UTILIZING A VALUE OF INFORMATION FRAMEWORK TO IMPROVE ORE COLLECTION AND CLASSIFICATION PROCEDURES

by

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The Kiruna mine extracts three ore types during its mining operations. Phosphorus and potassium are the main contaminants of the ore. The first part of this research identifies the existence of different types of ore misclassifications using a database containing ore extraction records from the Kiruna mine. The second part focuses on using these identified misclassification errors and a Kiruna cost model to quantify the cost of the misclassification errors to the Kiruna mine. We assume the principal cost of the errors is reflected in the under-utilization of the ore processing mills.

Utilizing a VOI framework, we examine the feasibility of purchasing a laser-induced fluorescence (LIF) analyzer as a source of additional information on extracted ore quality for the Kiruna mine. We find, given certain assumptions, that it is beneficial to the mine to purchase 10 LIFs (one for each production area). Depending on the accuracy of the LIF analyzer, the net benefit of the additional information on ore

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Chapter 1

INTRODUCTION

Every mine has the end goal of delivering an expected amount of product to its customers when promised. Uncertainties inherent to mining can make this goal difficult to meet. These uncertainties contribute to a number of operational problems including, choosing a mining method, planning extraction, predicting the quality and quantity of extracted ore and meeting production targets. In this research we focus on uncertainty in meeting production targets. Uncertainty in ore grade quality is one of the major contributors to the difficulty in meeting production targets.

Uncertainties in extracted ore grade quality are attributed to two causes: (i) geologic composition of the orebody and (ii) dilution of the ore during extraction. Geologic uncertainty concerns the quality of the orebody or the contents of the cave rock that surrounds the orebody. Dilution of the ore takes place during the actual mining process. In underground mining, as ore is recovered via a caving method (e.g., block caving, sublevel caving), a percentage of the available ore becomes diluted with contaminants in the ore and in the cave rock surrounding the orebody. The uncertainty in the amount of dilution leads to the unpredictability in the quantity and quality of collected ore. Both types of uncertainty can lead to missing production targets, thus affecting a mine's profitability as well as business relationships between the mining company and its customers.

The Loussavaara-Kiirunavarra Aktiebolag (LKAB) company operates a large underground iron ore mine north of the Arctic Circle in Kiruna, Sweden. Kiruna is the sole underground iron ore producer in the world today (Collins *et al.*, 2001). The mine extracts three ore types which are distinguished by their phosphorus (P), potassium (K_2O), and iron (Fe) contents. Phosphorus and potassium are the main contaminants of the ore. Kiruna's mining method (sublevel caving) leads to a high degree of ore dilution during recovery. This dilution creates uncertainty in the extracted ore type making it difficult to meet production targets. This research focuses on utilizing a value of information (VOI) methodology to analyze the value of gathering information on extracted ore quality. We use VOI to assist mine operators in making decisions regarding ore classification and collection procedures.

1.1 Literature Review

Decision makers seek the best way to determine when to mine, how to mine, which equipment to select, and how to terminate operations after a resource has been economically exhausted. These decisions are complex ones that combine scientific techniques and practical knowledge. The literature review reveals two approaches to modeling decision making in mining: 1) deterministic decision making models and 2) stochastic decision making models.

1.1.1 Deterministic Decision Making Models

Early mine modeling methods are deterministic in nature and have been used in project selection, mining method selection and equipment selection. The most common early deterministic model uses a static NPV calculation to compare costs versus benefits, given a number of assumptions such as orebody size and shape, amount of reserves, quality, and market prices. The type of NPV calculations used in early models does not account for uncertainty in revenues or costs. Studies that utilize this type of deterministic modeling are: Boshkov & Wright (1973); Laubscher (1981); Sevim & Sharma (1991); Markeset & Kumar (2000).

Recently, deterministic optimization models have become more popular. Included in this categorization are integer programming models (Çelebi, 1998), multi-criteria optimization models such as goal programming (Mukherjee & Bera, 1995), analytical hierarchy process (Samanta *et al.*, 2002), and fuzzy decision making theory (Bitarafan & Ataei, 2004). Nicholas (1981, 1992) ranks mining methods based on a number of key inputs. Genetic algorithms are also used to solve deterministic models such as integer programs (Haidar & Naoum, 1996; Haidar *et al.*, 1999).

Deterministic modeling is a scientific and mathematical method to assist decision makers. While uncertainty in input factors can be investigated to some extent using sensitivity analysis, it is virtually impossible to account for all uncertainty that is inherent in model input factors. Stochastic models allow decision makers to capture multiple sources of uncertainty at once.

1.1.2 Stochastic Decision Making Models

Simulation is the most well-known stochastic modeling method, and the most prominently applied in the mining sector. Examples of mining simulation models are found in Magalhaes *et al.* (1996); Sturgul (1996); Dimitrakopolous *et al.* (2002). Other stochastic modeling tools include: queueing theory (Kappas & Yegulalp, 1991; Zhonghou & Qining, 1988), expert systems theory (Clark *et al.*, 1990; Erdem *et al.*, 1996; Zhang *et al.*, 1998), reliability analysis (Hall *et al.*, 2000), and value of information (VOI).

Value of Information (VOI) Value of information is a type of stochastic decision making methodology aimed at quantifying the value of obtaining additional information to assist in reducing uncertainty. Value of information has been applied in decision making for many different purposes. A review of the literature finds that VOI is most commonly applied to five general areas: medicine, agriculture, veterinary science, business, and natural resources.

Researchers in the medical and veterinary fields utilize VOI to assist in decision making processes. Claxton *et al.* (2005) and Meltzer (2001) use decision analysis and a VOI methodology to support procurement of new medical advancements (medicines, tests, practices, etc.). Other notable studies in medicine include the design of clinical trials (Claxton & Thompson, 2001) and analyzing the use of pharmacoeconomics, i.e., economics applied to pharmaceutical studies (Miller, 2005). In veterinary science, VOI has been applied extensively to studies involving a number of different animal types. Lockhorst & Claassen (1997) investigate the value of collecting additional information on pig characteristics to organize pig fattening operations. Krieger & Hoehn (1999) use value of information to measure sport anglers' willingness to pay for information on chemical residue in fish. Additional references include studies on animal behavior (Koops, 2004) and investigating the risk of imported animal diseases (Disney & Peters, 2003). Disney & Peters (2003) reference a number of applications in both the veterinary and agricultural sectors. Agricultural studies include Meza & Wilks (2004); Minasny & McBratney (2002); Mitchell (2003).

VOI has also been used widely in business. Examples include game theoretical settings (Martin & Ho, 2002), stylized versions of real-world scenarios (Simchi-Levi & Zhao, 2003), and practical industrial applications. Walls *et al.* (1999) use a value of information methodology to evaluate different maintenance strategies for a Co-operative Telerobotic Retrieval (CTR) System for the Idaho National Engineering Laboratory (INEL). VOI is applied in designing control software in satellite antennae deployment (Norstrom *et al.*, 2002) where different control software designs are compared to reduce risk and uncertainty. Alles *et al.* (1998) investigate how division managers of a decentralized company can withhold information if they fear that it is detrimental to their interests.

The use of VOI in the mining sector is sparse. In the natural resource arena, VOI is applied most prominently to oil and gas exploration. Chermak & Patrick (1995) investigate a firm's decision making process in drilling natural gas wells. Their paper models and evaluates the economic benefits of an enhanced information technology that provides improved estimates of reservoir characteristics for an unconventional gas resource. The information is used to assess the well's potential and to determine how best to complete and produce the well. Bjørstad *et al.* (1989) create a stochastic dynamic model for making exploration decisions. They investigate the effect that gathering information over time has on the decision to explore, wait, or stop investing in exploration.

Applications of VOI in the mining sector are few. Peck & Gray (1999) make no explicit reference to VOI, yet discuss the potential benefits of gathering information to decision makers in the mining industry. Tulcanaza & Ferguson (2001) create a strategic development methodology designed to help decision makers choose between mineral development projects, specifically for Codelco-Chile (a major copper producer), though the authors stipulate the methodology could be applied to any mine. Though the authors refer to using "value of information," their methodology is not VOI in the traditional sense. While they place value on the information provided by each main development phase by comparing expected budget costs with the expected net present value, the authors fail to take into account uncertainty of information on the mineral specifications and reserves.

Barnes (1986) compares stochastic programming and VOI techniques in the incorporation of geostatistical estimation into mine planning. Typical estimates done via kriging provide not only a parameter estimate, but also a measure of the uncertainty associated with this parameter, the parameter variance. The author investigates geologic delineation sampling as a technology that has a cost and value associated with it. Mine operators must meet specified contract production requirements and satisfy certain quality constraints (e.g., percent sulfur content and percent ash content constraints).

Whereas Barnes investigated some methods to reduce uncertainty in a generic coal mine, this research actually applies the value of information technique to a working mine. Additionally, we develop a methodology for identifying the existence of misclassification errors in an ore extraction database, provided by Kiruna. The results of this research will provide mine managers with valuable insight into the decision on whether or not to purchase scanner technology that helps reduce extracted ore uncertainty.

Chapter 2

THE KIRUNA MINE AND ORE MISCLASSIFICATION

2.1 The Kiruna Mine

In approximately 1696, the first documented ore samples were collected in the Kiirunavaara and Luossavaara mountains located in northern Sweden, above the Arctic Circle. The vast wealth of ore discovered was not economically feasible for exploitation until the 1870's. In 1890 the Loussavaara-Kiirunavaara Aktiebolag (LKAB) company was formed. The Kiruna mine began as a surface mine. In 1957, mining operations started to move underground because of economic infeasibility of surface mining. Surface mining stopped completely by 1962. Currently, the main mining level is at 1045 meters below the surface. Kiruna produces approximately 65,000 tons of ore a day, amounting to about 24 million tons a year. The extracted ore is sent to one of four mills where the ore is processed to produce either fines or pellets used in steel manufacturing.[1]

The Kiruna orebody is a high-grade magnetite ore approximately four kilometers long and 80 kilometers wide (Kuchta, 2002). There are two main ore types located *in situ*. About 80% of the orebody contains a high iron, low phosphorus B type ore and the remaining 20% is a high phosphorus D type ore. The main contaminants of the orebody are phosphorus (P) and potassium (K_2O). Extraction of the two main

[1]Fines (sinter fines) are finely ground ore particulates. They are sintered to lump ore at the steel mills for use in blast furnaces. Pellets are sintered and compressed balls of ore of uniform quality. They are used directly in steel mill blast furnaces (LKAB, 2005).

types of ore yields three specific ore types: B1, B2, and D3. B1 ore is characterized by having a high iron content ($\sim 68\%$ on average), a low phosphorus level ($\sim 0.06\%$), and a potassium level lower than 0.15%. B2 ore is typically formed during the extraction process. The high iron, low phosphorus B1 ore mixes with waste rock, raising the phosphorus content of the ore, resulting in B2 ore. On average the B2 ore contains approximately $0.2\%P$ and more than 0.15% K_2O. The D3 ore has the highest levels of phosphorus, greater than $0.9\%P$ (Topal, 2003). Table 2.1 illustrates the average content of all key elements and usage of the three ore types. Note that phosphorus is the key factor that distinguishes the three ore types. Potassium content is important only when categorizing B1 ore.

Ore Type	**%P**	**%K_2O**	**Use**
B1	0.06	0.15	Fines production
B2	0.2	-	Medium (P) pellets feed
D3	0.9	-	High (P) pellets feed

Table 2.1. Characteristics of Three Ore Types (Topal, 2003)

2.2 Sublevel Caving and Ore Dilution

A number of different methods are used for underground mining including longwall, room-and-pillar, sublevel stoping, block caving and sublevel caving. The method chosen is often due to the economics of the project (costs versus benefits) and the specific geology of the orebody. The Kiruna mine uses large-scale sublevel caving for its mining operations.

Sublevel caving is a mass mining method that employs the concept of gravity flow to assist in ore recovery. Under optimal conditions, the sublevel caving method can recover 85 to 90% of the ore with 15 to 20% dilution (Boshkov & Wright, 1973). As with any mining method, sublevel caving has its advantages and disadvantages. Besides being one of the safest underground mining methods, the repetitive nature of sublevel caving (drifting, drilling and blasting, and recovery and transportation) and the use of trackless transport systems lends itself to a high degree of flexibility and automation (Kvapil, 1982). The major disadvantage of sublevel caving is the high amount of ore dilution that occurs during recovery. Figure 2.1 is a pictorial representation of a typical sublevel caving operation.

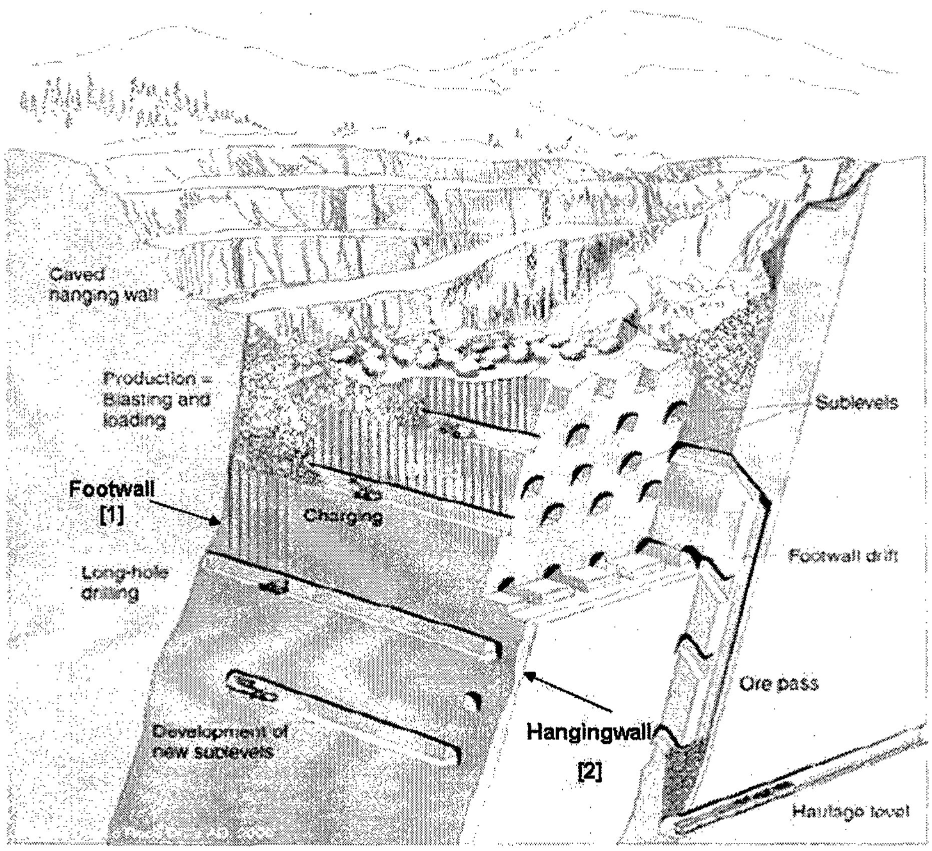

Figure 2.1. Representation of sublevel caving (www.atlascopco.com)

The topmost levels of Figure 2.1 represent the sublevels (or drifts) from which ore is currently extracted. Lower levels of the mine are prepared for blasting or development. Each sublevel is connected to a collection of ore passes where the ore is dumped and awaits transport by train to the crusher area. The process of sublevel caving is depicted pictorially in Figure 2.2 (LKAB, 2005). Each step of this process is described below.

1. *Preparation and Development*: New sections of the mine are prepared for ore extraction. Electric powered drills form drifts which extend from the footwall (see [1] on 2.1) to the hangingwall (see [2] on 2.1) through the orebody. Drifts can be up to 80 meters in length.

2. *Production Drilling*: After developing the drifts, production drilling commences. A fan-shaped pattern of 10 holes is drilled using a remote-controlled drill rig. The completed holes are loaded with explosives for blasting.

3. *Charging and Blasting*: A remote-controlled robot enters the drift and inserts explosives into the set of drill holes closest to the footwall. The holes are blasted and recovery vehicles, known as load-haul-dump units (LHDs), are sent into the drifts to recover the blasted ore. LHDs are electric, wheeled vehicles that carry approximately 25 tons of ore.

4. *Loading*: Once the LHD collects the ore, it drives to the end of the drift and dumps the ore into a collection bin, known as an ore pass. The ore waits there for transportation to the crushers.

5. *Hauling*: The main haulage level in Kiruna is the 1045m level. A remote-controlled train is sent to collect the ore from a full ore pass. A train consists

of about 24 cars and carries approximately 500 tons of ore. The train proceeds from the ore pass to the crushers.

6. *Crushing and Hoisting*: The train arrives at a crusher where the bottoms of the rail cars open and unload the ore. The ore is crushed for easier processing at the mills and is hoisted to the surface using an ore elevator known as a skip.

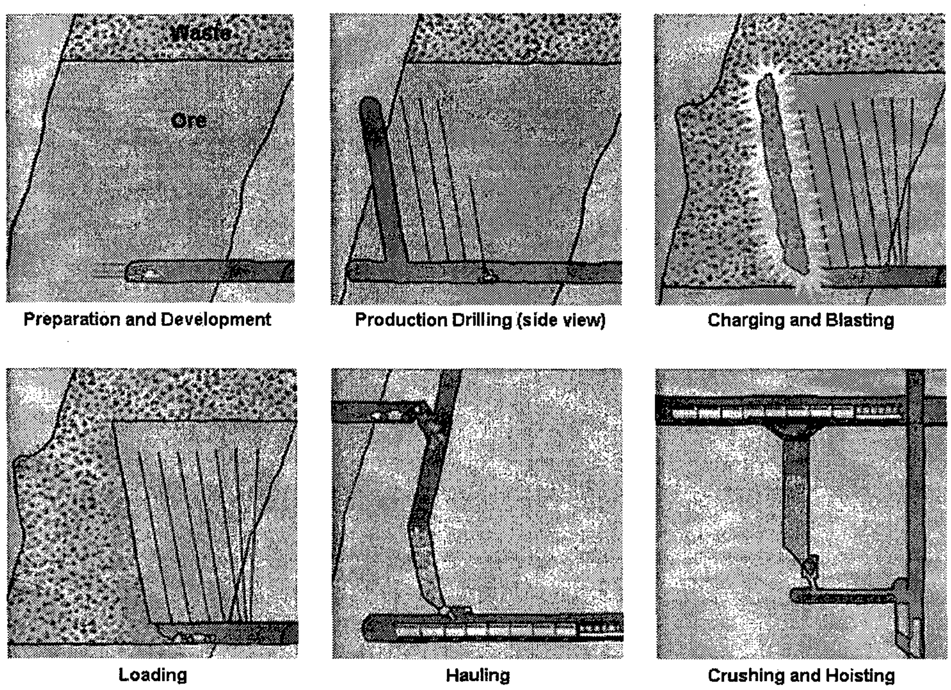

Figure 2.2. Detailed description of sublevel caving (www.lkab.com)

Mostly ore is collected during initial recovery after blasting. Gravity causes the waste rock to filter down to the recovery area, mixing with the ore. As the process continues, surrounding cave rock mixes with the ore and the levels of waste rock recovered start to rise. The waste rock causes dilution of the mined ore. Eventually, at a predetermined acceptable level of dilution (i.e., loads collected from a drift contain

50% ore and 50% waste), the mining of the drift is complete. The amount of ore dilution is difficult to predict because of the difficulty in modeling the gravity flow process.

Extracted Ore Grade Uncertainty at Kiruna

Through the assaying of core samples and 3D imaging systems, the mine operators have a fairly accurate idea of the composition of the intact orebody. With this information, Kiruna has developed an in-house computer program which estimates how many tons of each ore type to expect from each production area (Kuchta, 2002). From this information, the mine then generates a production schedule designed to meet demand, which is known with certainty. This schedule is then implemented throughout the mine production areas.

Load-Haul-Dump (LHD) units transport the blasted ore from current mining sites to an orepass. These orepasses are designated to collect a specific type of ore: B1, B2 or D3. It is critical to keep these ore types separated. If a load of D3 accidentally gets mixed into an orepass that is supposed to be collecting B1 ore, all ore in the shaft is contaminated and the entire load of B1 might change into B2 or D3 ore. This contamination delays the mine in meeting its B1 production targets and forces mine operators to attempt to compensate for that deficit, which may not always be possible given the areas of the mine currently undergoing extraction.

A train is sent to collect the ore once an orepass is full. The ore is then transported to the crusher area, where there are four crushers available. Each crusher processes a certain ore type. At any point in time, three crushers are crushing ore while the fourth is on standby in case of a crusher failure. While the ore is dumped from the train into the crusher it is assayed to obtain information on the chemical content of the ore, specifically $\%P$, $\%Fe$ and $\%K_2O$. This is the first time the composition of the extracted ore is realized and any misclassification is discovered. Once a misclassification is identified, the mine must modify its extraction plans in order to compensate for the misclassification. The next section details the data set received from Kiruna and how the uncertainty surrounding the composition of the extracted ore affects daily production.

2.3 Kiruna Data File

Kiruna provided a data file that contains every recorded ore extraction from September 2001 to June 2004, totaling 123,123 observations. Variables collected include: load number, date and time of load dumping, weight of ore load, crusher number, crusher ore classification (B1, B2, or D3), the shaft from which the ore was collected and its associated ore classification, and the assay information from each ore load. We use the variables included in Table 2.2 to analyze the data file provided. A list of all variables in the data file can be found in Appendix B.

Variable Name	**Label (Description)**
LoadNum	Load Number
Time	Time (24-hour Clock)
Date	Date
Weight	Weight of Ore Load (tons)
CrushNum	Crusher Number (4 crushers, 3 active at once)
CrushOre	Crusher Ore Quality (Crusher that processes B1, B2, or D3)
ShaftNum	Shaft Number
ShaftOre	Shaft Ore Quality (Shaft set to hold B1, B2, or D3)
PctWaste	Percent Waste Rock in Ore Load (assay result)
PctK2O	Percent Potassium Oxide in Ore Load (assay result)
PctFE	Percent Iron in Ore Load (assay result)
PctP	Percent Phosphorus in Ore Load (assay result)

Table 2.2. Names and Descriptions of Important Analysis Variables

The mine has monthly production goals for each ore type based on long-term customer contracts. The monthly goals are divided into daily goals based on the mine operators' knowledge of what ore types are expected from current mining areas. The first step in our analysis is to discover how well (or poorly) the mine is classifying the extracted ore. Currently, the extracted ore type is realized only after it is assayed at the crusher. The results of the assay are returned to the mine operators approximately ten minutes after the ore is dumped. By this time, the ore has been crushed and sent to the mills for processing. The delay in obtaining the assay results can lead to an error in classification of the ore that was dumped and in the corresponding shaft ore type classification. There is the possibility that the ore load dumped into the crusher is thought to be one type (e.g., B1) when it is actually another ore type (e.g., B2). The data file is used to capture these errors.

2.4 Misclassification Errors

A misclassification error is defined as follows: a load of ore of a certain quality is dumped into a crusher that processes a different ore quality. Mixing ore types can dilute more pure ore (e.g., B1) and change its chemical composition to a less pure ore type (e.g., B2 or D3). There are three types of identifiable misclassification errors: 1) errors due to mine operators attempting to maintain acceptable levels of the moving averages of key elements ($\%P$ and $\%K_2O$) of each ore type, 2) errors due to an inoperative crusher, and 3) errors due to the lag in shaft reclassification (because of the delay in ore contaminant information from the assay). Figure 2.3 provides a detailed view of Kiruna's current production level. Included are labels detailing the location and the meaning of the *ShaftOre* and *CrushOre* variables (see also Table 2.2). We use these variables to identify the various misclassification errors. After a brief description of each error type, we explain the methodology we use to find the errors, including pseudo-code, and follow with an example from the data file. In the pseudo-code, the step that identifies the error is highlighted.

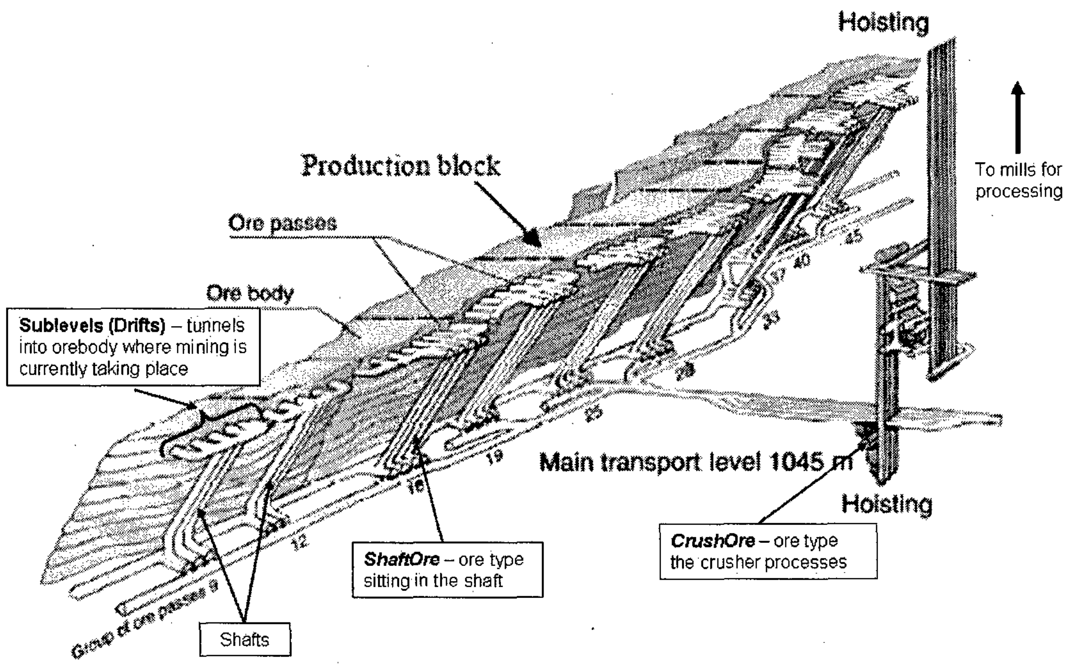

Figure 2.3. Kiruna Current Production Level

2.4.1 Error due to Fixing Moving Averages (E_A)

As each train load is processed, the mine updates the moving averages of the $\%P$ and $\%K_2O$ in each ore type. In order to maintain these averages within tolerance limits (see Table 2.1, Section 2.1), it is sometimes necessary to redirect one ore type to a crusher that processes another ore type. As an example, consider the following scenario. The moving average of $\%K_2O$ in processed B1 ore exactly matches the maximum tolerable level for B1 ($\sim 0.15\%$). Based on assay information obtained from the last train load from a specific shaft, the mine operators know that the next train load of B1 ore from that shaft might have a higher than average $\%K_2O$ content. This load could drive the current running average for B1 ore beyond desired limits. Therefore, the next load of B1 ore is dumped as B2 in order to maintain the moving average of $\%K_2O$ in B1 below its maximum tolerable level. We refer to this as an error due to fixing moving averages, E_A.

The most obvious instance of an ore misclassification in the data file is when *ShaftOre* $\neq$ *CrushOre*. This implies that the ore type gathered from the shaft is deposited into the crusher that processes a different ore type. Therefore, to find an error we look for instances where the ore type delivered from the shaft (represented by the *ShaftOre* variable in the data file) does not match the ore type the crusher processes (labeled as the *CrushOre* variable). In order to determine if the mine operators have intentionally sent the ore to the wrong crusher, the assay results from the dumped ore load must be compared to the moving averages of $\%K_2O$ and/or $\%P$ for both the ore type depicted with the *ShaftOre* variable and the ore type represented by the *CrushOre* variable. The moving averages are not shown in Figure 2.4. We calculate the moving averages of $\%K_2O$ and/or $\%P$ for each ore type from the assay results contained in the data file. We create columns that track the moving averages of $\%P$ and $\%K_2O$ for all three ore types. For purposes of this research, we consider the maximum allowable levels of $\%P$ and $\%K_2O$ for all ore types as listed in Table 2.1.

The pseudo-code for finding E_A is listed below.

1. Does *CrushOre* $\neq$ *ShaftOre*?

   Yes $\Rightarrow$ Proceed to step 2

2. **Do $\%P$ and/or $\%K_2O$ moving averages exceed limits?**

Yes ⇒ Mark as E_A - Error due to fixing moving averages

An example of a representation of E_A in the data set is shown in Figure 2.4. Consider the observation in row five in Figure 2.4. The *CrushOre* variable equals B2 and the *ShaftOre* variable equals B1; condition 1 is met. When checking the moving averages for an E_A error, we examine the moving average of the contaminants for both ore types; an ore load could be purposefully erroneously dumped in order to manipulate the moving averages in either the B2 ore or the B1 ore. A load of B1 ore could be dumped in the B2 crusher for one of two reasons. First, if the moving average(s) of $\%P$ and/or $\%K_2O$ are too high in the B1 ore at the mill (>0.06 $\%P$ or >0.15 $\%K_2O$), that load of B1 could be redirected to the B2 crusher. If the contaminant level in the B1 ore arriving at the crushers is close to the maximum allowable level, this ore load may be redirected so B1 ore with lower contaminant levels can be sent to the B1 mill. Second, the moving average of $\%P$ is too high in the B2 ore (>0.2 $\%P$). The lower phosphorus B1 ore is deposited into the B2 crusher in order to lower the moving average of the B2 ore to acceptable levels. If either of these conditions occurs, the observation is flagged as E_A. Row five in this example is listed as the load erroneously dumped. There are other possible reasons why the *CrushOre* and *ShaftOre* variables do not match.

Load Num	Time	Date	Weight	CrushOre	ShaftNum	ShaftOre	Lost Weight	Lost Ore
1	4:32:20	12/5/2002	657	B1	121	B1	-	-
2	6:15:49	12/5/2002	665	B1	121	B1	-	-
3	8:39:19	12/5/2002	683	B1	121	B1	-	-
4	9:57:28	12/5/2002	685	B1	121	B1	-	-
5	10:37:31	12/5/2002	641	B2	121	B1	641	B1
6	18:27:36	12/5/2002	727	B1	121	B1	-	-

Figure 2.4. Error Due to Fixing Moving Averages, E_A

2.4.2 Error Due to Inoperative Crusher (E_C)

If the mismatch in *CrushOre* and *ShaftOre* is not due to fixing the moving averages, it must be attributed to another cause. The second identifiable misclassification error is caused by a crusher being non-operational, denoted as E_C. At any time a crusher can fail and/or have to be removed for maintenance. In this case, the ore that would normally be dumped in that crusher must be redirected to another crusher. Consider the following example: the B1 crusher fails. Any trains carrying B1 ore are now directed to either the B2 or D3 crusher. Those loads of B1 ore are lost as other ore types. The standby crusher can be activated within a few minutes, so the error is assumed to affect only one train load.

As with finding E_A, the first step in identifying E_C is to check and see if the ore brought from the shaft is being sent to the appropriate crusher. Suppose a shaft currently contains B2 ore. A load is collected from the shaft and deposited into the crusher that processes B1 ore. The moving averages of $\%K_2O$ and/or $\%P$ are checked in both the B1 and B2 ore, as described in the previous section. After eliminating the possibility of error due to fixing the moving averages, we check the trend in the shaft ore classification. The last load delivered from the shaft and the next load collected from the shaft are both B2, suggesting the ore type in the shaft has not changed. Since the ore type in the shaft is constant and the only anomaly is that the ore load dumped into the B1 crusher, this would suggest the B2 crusher was inoperative at the time the load was delivered and the ore was redirected to the B1 crusher.

We create new variables to assist with analysis of the data set include *Last ShaftOre*, which represents the previous ore type delivered from the shaft, and *Next ShaftOre*, which is the ore type received from the shaft in the train load following the current load. The pseudo-code for finding E_C is listed below.

1. Does *CrushOre* $\neq$ *ShaftOre*?

   Yes $\Rightarrow$ Proceed to step 2

2. Do %P and/or $\%K_2O$ moving averages exceed limits?

   (a) Yes $\Rightarrow$ Mark as E_A - Error due to fixing moving averages

   (b) No $\Rightarrow$ Proceed to step 3

3. Does *ShaftOre* = *Last ShaftOre*?

   (a) Yes $\Rightarrow$ Proceed to step 4

   (b) No $\Rightarrow$ Process next observation

4. **Does *ShaftOre* = *Next ShaftOre*?**

   Yes $\Rightarrow$ Inoperative Crusher - E_C

In step 2 above, the possibility of an E_A error is eliminated and determining if the mismatch is due to E_C involves examining the trend of the ore classification in the shaft. If *Last ShaftOre* = *ShaftOre* = *Next ShaftOre*, it is an indication the ore type in the shaft has not changed. This is easily seen in Figure 2.5.

Load Num	Time	Date	Weight	CrushOre	ShaftNum	ShaftOre	Last ShaftOre	Next ShaftOre
1	4:32:20	12/5/2002	657	B1	121	B1	-	B1
2	6:15:49	12/5/2002	665	B1	121	B1	B1	B1
3	8:39:19	12/5/2002	683	B1	121	B1	B1	B1
4	9:57:28	12/5/2002	685	B1	121	B1	B1	B1
5	10:37:31	12/5/2002	641	B2	121	B1	B1	B1
6	18:27:36	12/5/2002	727	B1	121	B1	B1	-

Figure 2.5. Error Due to Inoperative Crusher, E_C

The load of B1 ore is deposited in the B2 crusher only in row five. This would indicate that the B1 crusher was not functioning when that load was delivered to the crusher area; thus, the load had to be dumped into the B2 crusher, and E_C is said to occur.

2.4.3 Error Due to a Lag in Shaft Reclassification (E_L)

The last identifiable cause for a misclassification error is due to a lag in shaft reclassification, denoted E_L. This error is related to the uncertainty in the ore type recovered due to the dilution of the ore caused by the gravity flow recovery method. The information on the contents of the shaft is not realized until the ore has been dumped, crushed and sent to the mill for processing.

There are two occurrences in the data set which could suggest an instance of E_L. The first depends on the inequality of the *CrushOre* and *ShaftOre* variables (*CrushOre* $\neq$ *ShaftOre*), designated as the lower bound on E_L. The second occurrence of E_L is based on the equality of these variables, and is referred to as the upper bound on E_L.

E_L - Lower Bound Identifying E_L follows the same logic as detailed in Sections 2.4.1 and 2.4.2; the first indication that an error has occurred is when *CrushOre* $\neq$ *ShaftOre*. If this mismatch is not attributed to fixing the moving averages, again, we must check the trend in the ore type from the shaft. If the ore type in the current load (where *CrushOre* $\neq$ *ShaftOre*) is the same ore type as the last load delivered from the shaft and the next load brought from the shaft is *different*, this could indicate a lag in the information from the assay on the actual ore type in the shaft. Suppose a load of ore is deposited into a crusher. When the assay is returned to the mine operators, it reveals the actual ore type is different than expected; an ore misclassification has occurred. The mine operators must manually input the change in the shaft ore type. At very busy times, changing the shaft ore classification can be delayed one ore load. The result is, although the next load from that shaft (after the misclassified ore load) is directed to the correct crusher, the data set does not reflect this because the shaft ore classification has not yet been changed.

First, we must check and make sure the mismatch between the *CrushOre* and the *ShaftOre* variables is not attributed to E_A. Second, we verify that the *ShaftOre* variable is equal to *Last ShaftOre.* After this condition is met, we need to check that *ShaftOre* does *not* equal *Next ShaftOre.* A change in shaft classification (indicated by *ShaftOre* $\neq$ *Next ShaftOre*) implies the type of ore in the shaft has changed.

The pseudo-code below explains how to find E_L in the data file.

1. Does *CrushOre* $\neq$ *ShaftOre*?

   Yes $\Rightarrow$ Proceed to step 2

2. Do $\%P$ and/or $\%K_2O$ moving averages exceed limits?

   (a) Yes $\Rightarrow$ Mark as E_A - Error due to fixing moving averages

   (b) No $\Rightarrow$ Proceed to step 3

3. Does *ShaftOre* = *Last ShaftOre*?

   (a) Yes $\Rightarrow$ Proceed to step 4

   (b) No $\Rightarrow$ Process next observation

4. **Does *ShaftOre* = *Next ShaftOre*?**

   (a) Yes $\Rightarrow$ Inoperative Crusher - E_C

   (b) **No $\Rightarrow$ Lag in Shaft Reclassification, E_L - lower bound**

Once moving averages has been eliminated as the cause of the mismatch between *CrushOre* and *ShaftOre*, it is imperative to check the classification trend of the shaft ore type. Figure 2.6 is an example of E_L - lower bound. In Figure 2.6, row four contains an instance in which *CrushOre* $\neq$ *ShaftOre*. The *ShaftOre* value from hasn't changed from the last observation (row three). However, the next observation of the *ShaftOre* variable (row five) is B2; the ore type in the shaft has changed. Suppose the assay information for load number three is returned to the mine operators and indicates the ore type from that shaft is now B2. The next load from that shaft (row four) is dumped into the B2 crusher; however, the shaft ore type value has not yet been changed in the computer system to reflect that the shaft ore type has changed to B2; the *ShaftOre* value is still B1. To confirm that there is a lag in shaft reclassification, the next value of *ShaftOre* (load number five) must be checked to verify that the classification has changed and that shaft is yielding B2 ore. If this is the case, the error is marked as E_L - Lower Bound. In Figure 2.6 load number three is the erroneously dumped ore load.

Load Num	Weight	CrushOre	ShaftNum	ShaftOre	Last ShaftOre	Next ShaftOre	Last Weight	Lost Weight	Lost Ore
1	657	B1	121	B1	-	B1	-	0	-
2	641	B1	121	B1	B1	B1	657	0	-
3	727	B1	121	B1	B1	B1	641	0	-
4	266	B2	121	B1	B1	B2	727	727	B2
5	502	B2	121	B2	B1	B1	266	0	-
6	508	B2	121	B2	B2	-	502	0	-

Figure 2.6. Error Due to Lag in Shaft Reclassification, E_L, Lower Bound

This instance of the lag in shaft reclassification errors is labeled as a lower bound because we know there are other instances of E_L that are not captured with the case of *CrushOre* $\neq$ *ShaftOre*, but rather by using the criterion that *CrushOre* = *ShaftOre*. This method of identifying E_L is the upper bound on the error.

E_L **- Upper Bound** This error is based on a different initial assumption than all other errors; finding E_L - upper bound depends on the condition *CrushOre* =

ShaftOre. A majority of the data set contains observations where the ore collected from the shaft is deposited in the correct crusher (e.g., B1 ore from a shaft is dumped into the B1 crusher). Sometimes, even though it appears the ore is dumped into the correct crusher, the lag in shaft ore type reclassification can still result in an erroneously dumped ore load. Suppose mine operators are collecting B1 ore from a shaft. A load is dumped into the B1 crusher and later the assay results of that ore load are returned to mine operators revealing the ore type dumped was actually B2. This means, the last load dumped into the B1 crusher was actually B2 ore; therefore a classification error has occurred. The mine operators change the shaft classification in the system and the next load of ore collected from the shaft is labeled B2 ore and directed to the B2 crusher. We consider this an upper bound on the error because we are potentially identifying more errors than have actually occurred. It is possible that the mining area around that shaft has changed and the ore type has abruptly changed. Though this does happen, it is rare and difficult to identify in the data set.

The pseudo-code for finding the upper bound on E_L is detailed below.

1. Does *CrushOre* = *ShaftOre*?

   Yes ⇒ Proceed to step 2

2. Does *ShaftOre* = *Last ShaftOre*?

   (a) Yes ⇒ Proceed to next observation

   (b) No ⇒ Mark previous observation as E_L - Upper Bound

Figure 2.7 portrays an instance of E_L - upper bound. In Figure 2.7 the first condition in the pseudo-code is met for every ore load. In row four the second condition is not met (*ShaftOre* ≠ *Last ShaftOre*). Because the ore type in the shaft has changed, the ore load delivered in row three is labeled as the incorrectly dumped ore load. In this example, B2 has erroneously been dumped into the B1 crusher. That ore load of B2 is lost because it has already been crushed and sent to the processing mill by the time the assay results are returned to the mine operators.

Load Num	Time	Date	Weight	CrushOre	ShaftNum	ShaftOre	Last ShaftOre	Lost Weight	Lost Ore
1	4:32:20	12/5/2002	657	B1	121	B1	-	0	-
2	10:37:31	12/5/2002	641	B1	121	B1	B1	0	-
3	18:27:36	12/5/2002	727	B1	121	B1	B1	0	-
4	20:10:59	12/5/2002	266	B2	121	B2	B1	727	B2
5	21:19:34	12/5/2002	502	B2	121	B2	B2	0	-
6	23:45:55	12/5/2002	508	B2	121	B2	B2	0	-

Figure 2.7. Error Due to Lag in Shaft Reclassification, E_L, Upper Bound

Figure 2.8 is a flowchart depicting the logic used to collect the different error types discussed. All programming was done using the *SAS* programming language, version 9.1, on a IBM AIX 5L UNIX server.

2.4.4 Compilation of Errors

Once these errors are identified, we can compare the amount of each ore type the mine produced (actual ore production) to the amount the mine could have produced if not for the misclassification errors (estimated ore production). Actual ore production is the total amount of ore dumped into a crusher. Even though the mine realizes that some ore loads are dumped erroneously as different ore types, if an ore load is deposited into a certain crusher, say the B1 crusher, it is processed as B1 ore, regardless of its actual ore type. The actual amount of B1 ore produced is a summation of the weight (in kilotons) of all loads dumped into the B1 crusher. Estimated ore production is illustrated in the following example. Estimated B1 ore includes all B1 ore *correctly* dumped into the B1 crusher plus all B1 ore that was erroneously dumped into the B2 or D3 crusher, as identified by the misclassification errors. The

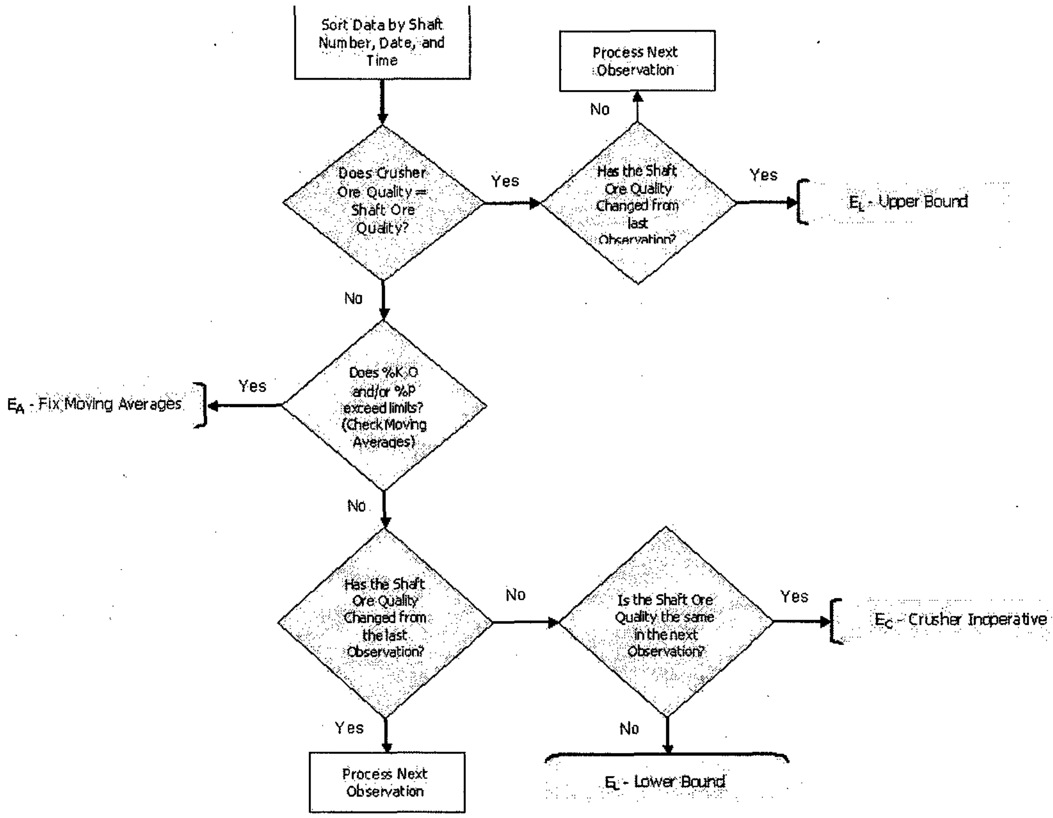

Figure 2.8. Flowchart for Logic Behind Identifying Misclassification Errors

calculations for actual and estimated ore produced are depicted in the equation below. Please note that all calculations for the reconstructed estimate of ore production are based on ex post data. Additionally, the equations are specific to B1; however, they can easily be changed for B2 and D3. A graphical representation of actual versus estimated production for B1 ore can be seen in Figure 2.9.

Actual B1 = All Ore Dumped into B1 Crusher

Estimated B1 = All B1 Correctly Dumped as B1 + All B1 Erroneously Dumped as B2 or D3

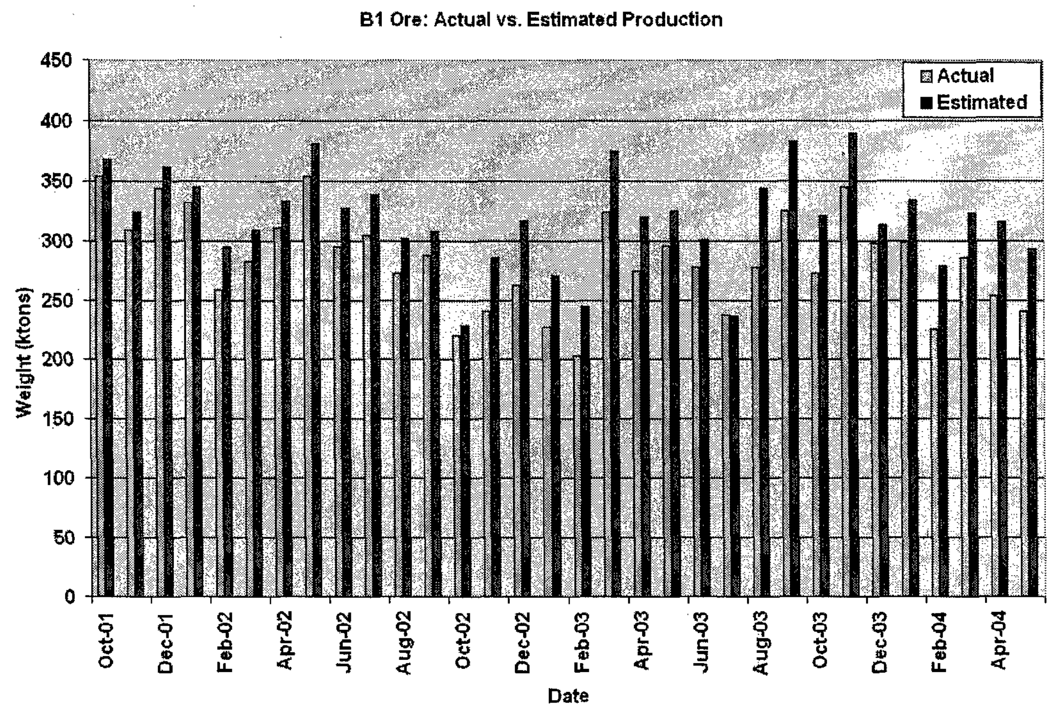

Figure 2.9. Representation of Actual Ore Production vs. Estimated Ore Production for B1 Type Ore

2.4.5 Measurement of Misclassification Errors

Once the misclassification errors are identified and quantified, we can assess the impact that these errors have on Kiruna's mining goals. We hope that additional information results in fewer misclassification errors, thus closing the gap between actual versus estimated production. Two different methods are used to measure the effect of the misclassification errors. We first examine how well the mine is meeting its production targets for each ore type. We find that for most months, the mine is underproducing B1 and B2 ore types. A percentage of this underproduction is caused by the misclassification errors. Second, we consider what the mine could have produced (in kilotons per month) had there been no misclassification errors. Figure 2.10 compares the actual and estimated production of B1 to monthly production targets for July and August 2002.

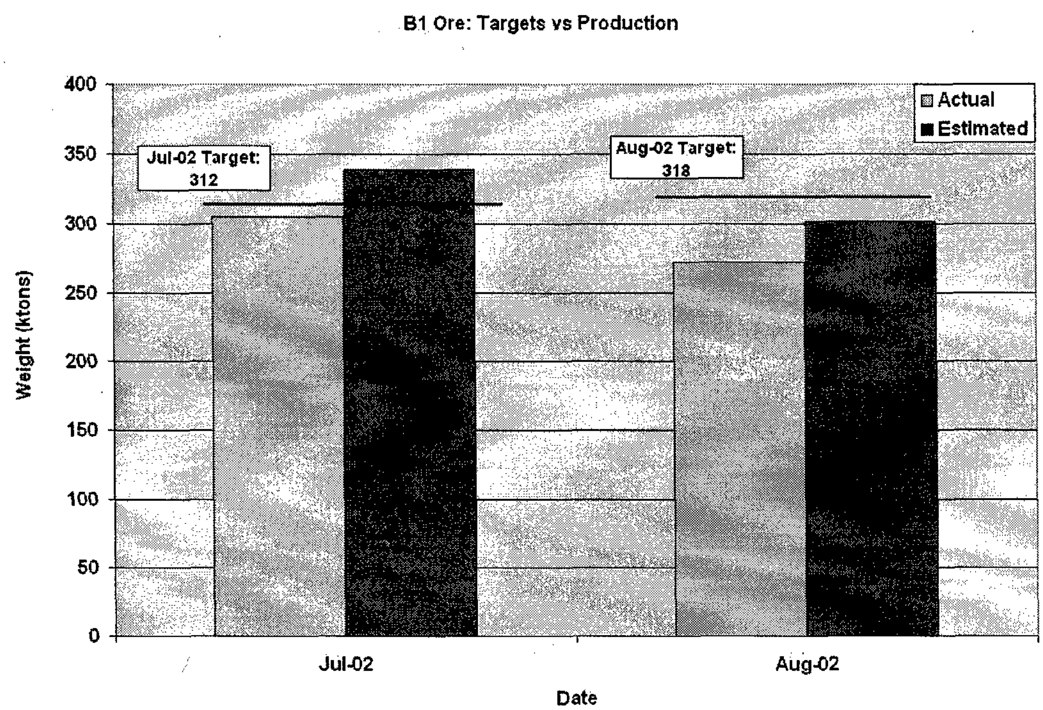

Figure 2.10. Comparison of Targets vs. Production - B1 Ore Type

In August 2002, the B1 production target was 318 ktons (kilotons) while the actual and estimated production were approximately 273 ktons and 302 ktons, respectively. The actual amount of B1 produced missed the target by 45 ktons (318-273). The mine would have missed its target by only 16 ktons (318-302), if not for the ore misclassification errors. Therefore, the errors account for approximately 64% ((45-16)/45 * 100) of the production shortfall.

In July 2002, the actual production level is below the target and the estimated level is above the target. This means, in absence of the misclassification errors, the mine should have processed more B1. In cases such as these, we say the errors account for 100% of the shortfall. The table below summarizes how the misclassification errors contributed to missing production targets for B1 and B2 ore types. Since all extracted ore is processed as one of three types, if B1 and B2 are underproduced, D3 is overproduced (see Appendix A).

Ore Type	Average % Shortfall Due to Misclassification
B1	56%
B2	12%

Table 2.3. Misclassification Errors and Production Shortfall

We can also measure the effect of the misclassification errors by calculating how much more or less the mine could have produced if not for the errors. Table 2.4 below illustrates these calculations. On average, 34.3 ktons and 26.1 ktons of additional B1 and B2 ore, respectively, could have been processed each month if all misclassification errors were eliminated.

Ore Type	Additional Monthly Production (ktons)
B1	34.3
B2	26.1

Table 2.4. Monthly Production Lost because of Misclassification Errors

Once we identify the misclassification errors, we want to quantify the significance of these misclassification errors to Kiruna. We are able to see that when Kiruna missed its production targets, it could approach, if not meet, the actual production targets if not for ore misclassification. With a solid understanding of the significance of the misclassification errors, these errors will now be used to quantify the cost of misclassification to the mine.

Chapter 3

UNDER-UTILIZATION OF ORE PROCESSING MILLS AND THE COST OF ORE MISCLASSIFICATION

There are costs associated with the Kiruna mine not meeting production targets because of ore misclassification. These costs include, but are not limited to, loss of goodwill with customers for not delivering products on time or of sufficient quality, ships sitting idle in the harbors waiting for the correct product, and the under-utilization of the ore processing mills due to misclassification. Due to the unavailability of representative data, quantifying the costs of loss of customer goodwill and the idleness of ships are not considered. This chapter focuses on the cost of the under-utilization of the mills.

3.1 Mill Under-utilization

Kiruna has four ore processing mills. Three are located at the Kiruna mine and one is located in nearby Svappavaara. One mill at Kiruna processes B1 ore; the other two process the high-phosphorus D3 ore. The mill at Svappavaara processes the B2 ore. Table 3.1 contains the mill naming convention used at Kiruna, the type of ore each mill processes and the corresponding capacity for each mill (provided by LKAB). For simplicity, in the remainder of this document, we refer to the mills using the ore type they process. For example, we refer to the SK mill as the B1 mill.

We use the actual ore production versus the estimated ore production derived from the calculations presented in Section 2.4.4 and the capacity numbers in Table

Mill Name	Ore Type Processed	Max Production Rate (ktons/day)
SK	B1	15.72
Svappis	B2	12.0
KK2	D3	12.72
KK3	D3	16.2

Table 3.1. Capacities of the Kiruna Mills (Griffiths, 2005)

3.1 to calculate the actual and estimated utilization for the Kiruna mills (reference Table 3.2). Since the extraction data file does not distinguish to which D3 mill the ore from the D3 crusher is sent, we report only a single utilization value for both D3 mills combined. Because of this lack of distinction, we hereafter use aggregated values (e.g., utilization, costs, ore loads) for the D3 mills.

The actual mill utilization is the ratio of 1) the average amount of ore actually produced in a month (averaged monthly from 2001-2004 using the Kiruna ore extraction data file) to 2) the monthly capacity of the mill. We convert this ratio to a percentage utilization by multiplying by 100. For example, the actual B1 production monthly average is 278 ktons. The average monthly capacity for the B1 mill is 478 ktons. The utilization of the B1 mill is calculated using the equation below. The actual utilization of the B2 and D3 mills is calculated in a similar manner.

$$\begin{aligned}\text{B1 Mill Actual Utilization} &= \frac{\text{B1 avg. actual monthly prod.}}{\text{B1 avg. monthly capacity}} * 100 \\ &= \frac{278\text{ ktons}}{478\text{ ktons}} * 100 = 58\%\end{aligned} \tag{3.1}$$

Misclassification errors lead to an under-utilization of the mills because less ore is sent to the mill than expected for the B1 and B2 mills. The D3 mill operates at greater than planned utilization because more ore is sent to that mill than expected.

The estimated mill utilization is the ratio of 1) the average amount of estimated ore produced per month (if not for misclassification) to 2) the average monthly capacity of the mill. The equation below details this calculation for the B1 mill. The estimated utilization for the B2 and D3 mills is calculated using a similar formula.

$$\begin{aligned}\text{B1 Estimated Mill Utilization} &= \frac{\text{B1 avg. estimated monthly prod.}}{\text{B1 avg. capacity}} * 100 \quad (3.2)\\ &= \frac{315\text{ ktons}}{478\text{ ktons}} * 100\\ &= 66\%\end{aligned}$$

The difference between the actual mill utilization and the estimated mill utilization is the percentage of mill under- (or over-) utilization due to ore misclassification. Considering the B1 mill, if there were no misclassification errors, the mill would operate at 66% of capacity (reference Equation 3.2). However, because of the misclassification errors, the B1 mill operates at an actual utilization of 58% (reference Equation 3.1). Therefore, misclassification causes the mill to operate at 8% below its estimated utilization, rather than at the highest observed percentage, which, in the case of the B1 mill, is 66%. The under-utilization due to misclassification is a lower bound on the under-utilization of the mills because of the possibility that the mills are capable of operating at 100% of capacity.

Utilization	**B1 Mill**	**B2 Mill**	**D3 Mills**
Actual	58%	95%	99%
Estimated	66%	103%	92%
Difference Due to Misclassification	8%	8%	-7%

Table 3.2. Utilization Comparison of the Mills (Griffiths, 2005)

There are three points to make about Table 3.2. First, the estimated utilization of the B2 mill is 103%. This suggests that if misclassification errors were corrected, there would be enough B2 ore to require that the B2 mill process at 103% capacity. Second, the actual and estimated utilizations for the two D3 mills are aggregated into a single utilization number. Third, while the B1 and B2 mill utilizations increase in the absence of misclassification errors, the utilization of the D3 mills decrease because less ore is directed to the D3 mills when the misclassification errors are corrected.

Given the percentage of mill under-utilization, we determine the cost of this under-utilization due to ore misclassification.

3.2 Cost of Mill Under-Utilization

The World Mine Cost Data Exchange (WMCDE) is an internet-based resource that provides comprehensive cost models for the world's major metal markets. These cost models are "based on verifiable engineering and production data and peer review by mining industry analysts from around the world" (World Mine Cost Data Exchange, 2005). As opposed to being simply a cost database, the WMCDE uses industry information to construct comprehensive cost models. Formulas embedded in the cost model allow users to change numerous factors (mining and milling rates, labor productivity, treatment costs, input costs, exchange rates, etc.) and determine how these changes affect mine operations (output, costs, profits, etc.) We obtained a Kiruna cost model from the WMCDE which contains information on profits, ore prices and a detailed breakdown of Kiruna operating costs at the mine and the mill. One difficulty with using the cost model is that the model aggregates the cost data for the three mills on site at the Kiruna mine (the B1 and the two D3 mills). There is no clear distinction as to which costs are specific to the B1 mill and which are specific to the D3 mills. Therefore, the costs for the under-utilization of the B1 and D3 mills are estimates based on our understanding of the relative capacities of the three mills and consultation with Kiruna mine personnel. We use the WMCDE cost model to assist in determining the cost of mill under-utilization.

We suggest that the cost of mill under-utilization consists of three components: 1) profits forgone, 2) the fixed cost of mill under-utilization and 3) the variable cost of mill under-utilization. The total cost of mill under-utilization is given in Equation 3.3 below.

$$\begin{aligned} \text{Total Cost}_{ij} &= \text{Profits Forgone}_{ij} + \text{Fixed Cost}_{ij} + \text{Variable Cost}_{ij} \\ &\quad \forall\ i \in \{\text{B1, B2, D3}\}, \quad j \in \{\text{B1M, B2M, D3M}\} \end{aligned} \tag{3.3}$$

where

$$\begin{aligned} i &: \ \text{ore type} \ \in \{\text{B1, B2, D3}\} \\ j &: \ \text{mill type} \ \in \{\text{B1M, B2M, D3M}\} \\ \text{Profits Forgone}_{ij} &: \ \text{profits forgone of ore type } i \text{ sent to mill } j \text{ (\$ per train)} \\ \text{Fixed Cost}_{ij} &: \ \text{fixed cost for ore type } i \text{ sent to mill } j \text{ (\$ per train)} \\ \text{Variable Cost}_{ij} &: \ \text{variable cost of ore type } i \text{ sent to mill } j \text{ (\$ per train)} \end{aligned}$$

We calculate the cost of mill under-utilization for each mill and ore combination. When the ore type and the mill type match (i.e., B1 ore is sent to the B1 mill) we say there is no cost because the ore has not been misclassified. The sections below detail each component of the total cost of mill under-utilization and we calculate this total cost for each of the nine mill and ore combinations.

3.2.1 Profits Forgone

The first component in the equation for the cost of mill under-utilization is the profits forgone, which are the profits lost because of ore misclassification. We calculate the profits forgone as the product of 1) the margin (the price of the ore minus the cost of the ore production) and 2) the average amount of ore in a train load that arrives at the crusher. We calculate the average amount of ore in a train load arriving at the crusher (approximately 455 tons) from the Kiruna extraction data base. The calculation for profits forgone is given in Equation 3.4 below.

$$\text{Profits Forgone}_{ij} = \mathrm{m}_{ij} * \mathrm{a} \tag{3.4}$$

$$\mathrm{m}_{ij} = \begin{cases} \mathrm{p}_i - (\mathrm{c}_i^1 + \mathrm{c}_i^2), & \mathrm{ord}(i) \neq \mathrm{ord}(j) \\ 0, & \mathrm{ord}(i) = \mathrm{ord}(j) \end{cases}$$

$$\forall\ i \in \{\mathrm{B1},\ \mathrm{B2},\ \mathrm{D3}\}, \quad j \in \{\mathrm{B1M},\ \mathrm{B2M},\ \mathrm{D3M}\}$$

where

a : number of tons in an average train load (tons per train)

c_i^1 : mine cost for ore type i ($ per ton)

c_i^2 : mill cost for ore type i ($ per ton)

p_i : price for ore type i ($ per ton)

m_{ij} : margin for ore type i sent to mill j ($ per ton)

We use the ord() function to determine how to calculate the margin. The ord() function returns the position number for an element in a set. For example, considering the set of ore types (indexed by i), ord(B1) = 1, ord(B2) = 2, and ord(D3) = 3. In the first instance of calculating the margin, the condition states this calculation is computed if ord(i) $\neq$ ord(j). This means that the position of the element in the set of ore types is not equal to the position of the element in the set of mill types (indexed by j). For example, the margin would be calculated under this circumstance if i = B1 [ord(B1)=1] and j = B2M [ord(B2M)=2]. The second case for calculating the margin is under the instance where ord(i)=ord(j). This equality indicates the correct ore is sent to the correct mill, i.e., there is no misclassification, and there is no cost for this action.

In calculating the profits forgone, we disregard any profits that might be made by selling the misclassified ore as a different ore type. Because the Kiruna mine attempts to produce just enough ore to meet demand, we assume that there is no spot market for any ore produced over the mine's target. For example, if a load of B2 is deposited into the B1 crusher, the mine loses the profits it could have made from processing the ore as B2, but we don't consider the profits made by processing the B2 ore as B1. Table 3.3 contains the costs, prices and margins for the three ore types, averaged from 2001 - 2004.

Using Equation 3.4, we calculate the profits forgone for each of the nine mill and ore type combinations. We detail these calculations in Table 3.4.

$/ton	Mine Cost	Mill Cost	Price	Margin
Fines (B1)	$7.90	$9.52	$21.64	$4.22
Svappavaara Pellets (B2)	$9.12	$11.00	$36.64	$16.52
Kiruna Pellets (D3)	$10.16	$12.24		$14.24

Table 3.3. **Cost and Price Comparison for the Three Ore Types.** We calculate the mining costs, milling costs and prices from the cost model. The last column, the margin, is the difference between the price and the mine and mill costs. That is, margin = price - (mine cost + mill cost).

Mill (1)	**Ore Type** (2)	**Average Train Load (tons/train)** (3)	**Margin ($/ton)** (4)	**Profits Forgone ($/train)** (5)
B1 Mill	B1 Ore	455	$0	$0
B1 Mill	B2 Ore	455	$16.52	$7,517
B1 Mill	D3 Ore	455	$14.24	$6,479
B2 Mill	B1 Ore	455	$4.22	$1,920
B2 Mill	B2 Ore	455	$0	$0
B2 Mill	D3 Ore	455	$14.24	$6,479
D3 Mill	B1 Ore	455	$4.22	$1,920
D3 Mill	B2 Ore	455	$16.52	$7,517
D3 Mill	D3 Ore	455	$0	$0

Table 3.4. **Calculation of Profits Forgone ($/train).** Column one (1) is the mill type. Column two (2) is the ore type that is sent to that mill. Column three (3) is the average amount of ore in a train load arriving at the crusher area. Column four (4) is the margin for the ore in column two (reference Table 3.3). The fifth column (5) is the calculation of the profits forgone (average train load (3) * margin (4).)

The fixed cost of mill under-utilization is the second component in determining the total cost of mill under-utilization.

3.2.2 Fixed Cost of Mill Under-utilization

The fixed cost of mill under-utilization consists of mill services (air, water, etc.) and mill administration, which we calculate from the Kiruna cost model. Even though the mill is producing at less than capacity, the mine must still pay the fixed cost associated with mill operations. The closer a mill operates to capacity, the greater the proportion of the fixed cost covered by revenue made from selling the end product. Because the cost data are aggregated for the B1 and D3 mills at Kiruna, we have to allocate the fixed costs between the B1 mill and the D3 mills. We proportion the fixed costs based on the capacities (reference Table 3.1) of the mills. We calculate the total capacity for all mills at the Kiruna mine (not including the B2 mill at Svappavaara), and each mill capacity is a portion of this total capacity. An example of this calculation is presented in the equation below.

$$\begin{aligned}
\text{B1 Proportion of Fixed Cost} &= \frac{\text{Capacity of SK}}{\text{Cap. of SK} + \text{Cap. of KK2} + \text{Cap. of KK3}} \\
&= \frac{15.72}{15.72 + 12.72 + 16.2} \\
&= 0.35 \quad \Longrightarrow \quad 35\%
\end{aligned}$$

The B1 mill accounts for 35% of total processing capacity, while the D3 mills account for 65% of capacity. These percentages are then multiplied by the total fixed cost at the Kiruna mine to get the fixed cost at each mill, as shown for B1 in the equation below. The D3 mills' fixed cost is calculated in a similar manner by substituting 0.65 for 0.35. The fixed costs (reported in dollars per day in the cost model) for each mill are displayed in Table 3.5.

$$\begin{aligned} \text{B1 Mill Fixed Cost} &= \text{B1 Proportion of Fixed Cost} * \text{Total Kiruna Fixed Cost} \\ &= 0.35 * \$28,918 = \$10,183 \text{ per day} \end{aligned}$$

Mill	Fixed Cost ($/day)
B1	$10,183
B2	$10,477
D3	$18,734

Table 3.5. **Fixed Cost at the Ore Processing Mills ($/day).** The fixed cost for the B2 mill is extracted from the Kiruna cost model. The fixed costs for the B1 and D3 mills are estimated from the aggregated fixed cost in the cost model using their relative capacities. We report one representative fixed cost number for both D3 mills.

The fixed cost of ore misclassification for a mill is the difference between the fixed cost of the expected utilization of the mill and the fixed cost of the actual utilization of the mill, which we have termed the under-utilization due to misclassification (Table 3.2). Therefore, the calculation of the fixed cost of misclassification is the fixed cost of the mill to which the misclassified ore should have been sent multiplied by the percent under-utilization of that same mill due to misclassification, which is illustrated in the equation below.

$$\text{Fixed Cost}_{ij} = \begin{cases} \max\{\mathrm{e}_{j'} - \mathrm{a}_{j'}, 0\} * \mathrm{f}_{j'}, & \mathrm{ord}(i) \neq \mathrm{ord}(j) \text{ and } \mathrm{ord}(j')=\mathrm{ord}(i) \\ \\ 0, & \mathrm{ord}(i)=\mathrm{ord}(j) \end{cases} \quad (3.5)$$
$$\forall\ i \in \{\text{B1, B2, D3}\}, \quad j, j' \in \{\text{B1M, B2M, D3M}\}$$

where

$a_{j'}$: actual utilization of mill j'

$e_{j'}$: estimated utilization of mill j'

$f_{j'}$: fixed cost of mill j' (\$/day) (reference Table 3.5)

The maximize function results in a positive fixed cost if the estimated utilization of the mill is greater than the actual utilization and zero cost if the estimated utilization is less than the actual utilization. Since the utilization of the D3 mill decreases in the absence of misclassification errors, there is no fixed cost of under-utilization of the D3 mill in the event of misclassification. In the first instance of calculating fixed costs two conditions must be met: 1)ord(i) $\neq$ ord(j), and 2) ord(j') = ord(i). These conditions ensure that the fixed cost is calculated for the correct mill. For example, we calculate the fixed cost for B1 ore (i = B1) sent to the B2 mill (j = B2) as the fixed cost for the B1 mill because that is the mill that is under-utilized as a result of the misclassification. Table 3.6 details the fixed cost of mill under-utilization for the nine mill and ore combinations.

Mill (1)	Ore Type (2)	Mill Affected by Misclassification (3)	Fixed Cost ($/day) (4)
B1 Mill	B1 Ore	N/A	$0
B1 Mill	B2 Ore	B2 Mill	$838
B1 Mill	D3 Ore	D3 Mill	$0
B2 Mill	B1 Ore	B1 Mill	$815
B2 Mill	B2 Ore	N/A	$0
B2 Mill	D3 Ore	D3 Mill	$0
D3 Mill	B1 Ore	B1 Mill	$815
D3 Mill	B2 Ore	B2 Mill	$838
D3 Mill	D3 Ore	N/A	$0

Table 3.6. **Calculation of Fixed Cost of Mill Under-utilization ($/day).** The first column (1) is the mill to which the ore is sent. The second column (2) is the ore type that is sent to the mill. Column three (3) is the mill affected by the under-utilization due to misclassification, and the fourth column (4) is the fixed cost for the mill underutilization, as calculated with Equation 3.5.

The final factor in the cost of mill under-utilization due to ore misclassification is the variable cost.

3.2.3 Variable Cost of Mill Under-utilization

The variable milling costs are the supply and equipment operating costs associated with the following processes: reagent use, magnetic separation, wet high intensity magnetic separation, concentrate thickening and floatation, and pelletizing. These processes are used for producing pellets at the B2 and D3 mills only. Though there are other variable costs at these mills, the processes listed account for the majority of these costs.

There are also common variable costs associated with processing ore at all mills (e.g., crushing and grinding); these costs are approximately the same per ton of ore.

We consider these common variable costs sunk costs, and therefore we ignore them and our analysis considers only the variable costs that differ between mills.

The supply cost of the aforementioned processes consists of electricity costs (99%) and some media (grinding balls) costs (1%). The equipment operating cost consists of repair parts (95%), lube (4%), and wear materials (drill bits and liners) (1%). The variable costs in the cost model are reported in dollars per day. We calculate the average tonnage processed per day at a mill from the Kiruna extraction file and convert the variable costs to dollars per ton. The variable cost for each mill is listed in Table 3.7.

Mill	**Variable Cost ($/ton)**
B1	$0
B2	$0.30
D3	$0.59

Table 3.7. **Variable Cost for Ore Processing Mills ($/ton).** The variable costs of the B2 and D3 mills are a compilation of the costs associated with the following processes: reagent use, magnetic separation, wet high intensity magnetic separation, concentrate thickening and floatation, and pelletizing. Common variable costs associated with processing (crushing and grinding) at all mills are considered sunk costs; thus the variable cost at the B1 mill is $0.

The variable cost of ore misclassification is the difference between the variable cost of the mill to which the ore was sent and the variable cost of the mill to which the ore should have been sent, multiplied by the average tonnage of ore in a train load. In the event that B2 or D3 are sent to the B1 mill, the difference between variable costs would be negative. Since it isn't practical to assume that the mill incur a negative cost, we consider the variable cost of the misclassification to be zero. The variable cost calculation is provided below.

$$\text{Variable Costs}_{ij} = \begin{cases} (\mathrm{v}_j - \mathrm{v}_{j'}) * \mathrm{a}, & \mathrm{ord}(i) < \mathrm{ord}(j) \text{ and } \mathrm{ord}(j')=\mathrm{ord}(i) \\ 0, & \mathrm{ord}(i) \geq \mathrm{ord}(j) \end{cases} \tag{3.6}$$

$$\forall\ i \in \{\text{B1, B2, D3}\}, \quad j, j' \in \{\text{B1M, B2M, D3M}\}$$

v_j : variable cost of ore processing at mill j

$\mathrm{v}_{j'}$: variable cost of ore processing at mill j'

Table 3.8 details the variable costs for each of the nine mill and ore type combinations.

Mill (1)	**Ore Type** (2)	**Avg. Train Load** **(tons/train)** (3)	**Difference in Variable Cost** $(v_j - v'_j)$ **($/ton)** (4)	**Total Variable Cost** **($/train)** (5)
B1 Mill	B1 Ore	455	$0	$0
B1 Mill	B2 Ore	455	$0	$0
B1 Mill	D3 Ore	455	$0	$0
B2 Mill	B1 Ore	455	$0.30	$137
B2 Mill	B2 Ore	455	$0	$0
B2 Mill	D3 Ore	455	$0	$0
D3 Mill	B1 Ore	455	$0.59	$268
D3 Mill	B2 Ore	455	$0.29	$132
D3 Mill	D3 Ore	455	$0	$0

Table 3.8. **Calculation of Variable Cost ($/train)** The first column (1) is the mill to which the ore is sent. Column two (2) is the ore type sent to the mill. Column three (3) is the average tonnage in a train. Column four (4) is the variable cost of misclassification in dollars per train load, as calculated with Equation 3.6. The fifth column (5) is the total variable cost, which is the average tonnage per train (3) multiplied by the variable cost of misclassification (4).

Table 3.9 provides a summary of the costs when there is a misclassification of ore, where the total cost is as calculated in Equation 3.3. We have converted the fixed costs from dollars per day to dollars per train load by multiplying the fixed costs by the reciprocal of the average number of trains per day (125).

In the above discussion we develop a methodology to quantify the cost of ore misclassifications. The cost of ore misclassification is critical for evaluating the decision of whether to purchase technology that could be used to reduce misclassification errors. We apply the misclassification costs in a value of information framework used

Mill	**Ore Type**	**Profits Forgone ($/train load)**	**Fixed Cost ($/train load)**	**Variable Cost ($/train load)**	**Total Cost ($/train load)**
B1 Mill	B1 Ore	$0	$0	$0	$0
B1 Mill	B2 Ore	$7,517	$6.67	$0	$7,524
B1 Mill	D3 Ore	$6,479	$0	$0	$6,479
B2 Mill	B1 Ore	$1,920	$6.52	$137	$2,064
B2 Mill	B2 Ore	$0	$0	$0	$0
B2 Mill	D3 Ore	$6,479	$0	$0	$6,479
D3 Mill	B1 Ore	$1,920	$6.52	$268	$2,195
D3 Mill	B2 Ore	$7,517	$6.67	$132	$7,656
D3 Mill	D3 Ore	$0	$0	$0	$0

Table 3.9. **Calculation of Total Cost of Mill Under-utilization ($/train load).** The total cost for each mill and ore combination is the sum of the profits forgone, the fixed cost and the variable cost. The fixed cost has been converted from dollars per day to dollars per train load by multiplying by the reciprocal of the average number of train loads per day (125). The total cost has been rounded to the nearest dollar.

to help decision makers investigate the economic feasibility of acquiring additional information on ore grade type.

Chapter 4

VALUE OF INFORMATION

The previous chapter detailed how we determine the cost of the misclassification errors inherent to Kiruna's current mining practice. Specifically, we determine the cost of under-utilization of the mills due to misclassification. This under-utilization cost consists of three components: 1) profits forgone from misclassified ore, 2) the fixed cost of mill under-utilization and 3) the variable cost of mill under-utilization. We use these costs to assist us in determining the value of obtaining additional information on extracted ore quality.

We use a value of information analysis to assess the value of a scanner technology. This scanner would assay the ore before depositing it into an orepass as opposed to waiting until the ore is dumped into the crusher. To determine the value of the scanner we compare the expected value of the scanner to its purchase price and maintenance costs. We report the cost of mill under-utilization in dollars per train load for expositional purposes. The resulting expected value of the scanner is also in dollars per train load. We then convert these results to dollars in order to compare the expected benefits of reducing ore grade uncertainty to the cost of purchasing and maintaining the scanner. Given the information from the analysis, decision makers can determine whether or not the scanner is worth purchasing. If we show the scanner saves the mine money by reducing misclassification errors and this savings is greater than the purchase price and maintenance cost of the scanner, decision makers will be motivated to purchase it.

4.1 Kiruna's Current Operation

Figure 4.1 depicts the current decisions and uncertainties mine operators face when a train arrives at the crushers. A decision is made to dump the ore in a specific crusher based on an assumption as to what ore type the train currently contains. Mine operators form this assumption based on the last ore type observed from the same shaft. If the last train load from that shaft contained B1 ore, the mine operators assume that the current train load from that shaft also contains B1 ore.

Before the ore is dumped into the crusher, there is uncertainty as to the actual ore type, which is not resolved until the assay results are received. We represent the mine operators' decision through the use of a decision tree, shown in Figure 4.1. In the decision tree, the square represents a set of decision alternatives the mine operators must make when a train arrives at the crushers. The mine operators decide to direct the train to dump the ore in either the B1, B2, or D3 crusher. After this decision is made, the circles represent the uncertainty as to the actual ore type contained in the train. A load dumped into any crusher is realized as either B1, B2 or D3 ore. In this representation of the mine operators' decision, we assume they have an expectation that B1 is contained in the current train load.

The probabilities on the uncertainty branches represent the proportion of time that the actual ore type is B1, B2 or D3, given the mine operators expect the train to contain B1 ore. That is, given that the current train load is expected to carry B1, 84.9% of the time the train contains B1 ore, 11.1% of the time it contains B2 ore and 4% of the time it contains D3 ore. We use the Kiruna extraction data coupled with the identified ore misclassifications to calculate these probabilities (reference Chapter 2). Since these probabilities are calculated from the database, which is a sample of representative data, they are estimates of the actual probability of each event occurring. Each estimate has a certain amount of uncertainty surrounding it. However, the sample sizes are very large for each calculated probability (the smallest sample is approximately 18,000 data points); therefore, the variances around the estimates are very small. From a statistical perspective, the uncertainty surrounding each probability is negligible.

For each instance on the tree where the ore is deposited into the correct crusher, the cost of misclassification is zero. If the ore is deposited into the incorrect crusher (e.g., B1 ore into the B2 or D3 crusher), the cost associated with this misclassification follows Equation 3.3 (Section 3.2). For example, if B1 is dumped into the B2 crusher, the cost associated with this decision is the sum of the profits forgone of the misclassified B1 ore plus the fixed cost of the under-utilization of the B1 mill, and the extra variable cost incurred because of processing the B1 ore as B2 ore. Using the probability and costs of each outcome, an expected cost is calculated for each decision, represented by the "Chance" value. For example, given the mine operator choses to deposit the ore in the B2 crusher, the expected cost for this decision is $2,011. The objective of the decision tree is to minimize cost, so the optimal choice is to select the branch with the lowest "Chance" value. This choice is represented with the "Decision" label.

Based on the above decision tree, the best alternative (indicated in Figure 4.1 with the "TRUE" label on the branch) is to deposit the assumed B1 ore load into the B1 crusher, with an expected value of $1,094 per train load. This is the best alternative because it is the decision branch with the lowest cost.

There is an opportunity for the mine to purchase technology that will provide information that may reduce the uncertainty in the extracted ore grade. There are two types of information that can be used to reduce the uncertainty inherent in the

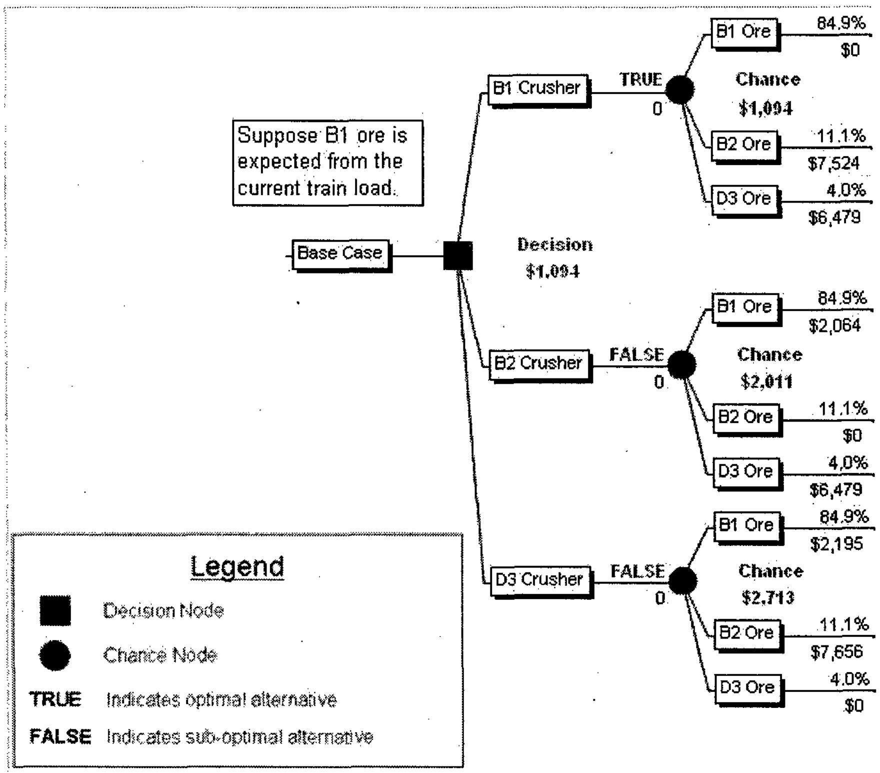

Figure 4.1. **Base Case Decision Tree**. This decision tree depicts the decisions and uncertainties of the mine operators' current decision when a train brings a load of ore to the crushers. The costs on each branch are the costs reported in Table 3.9.

decision making process - perfect and imperfect information. We investigate the impact of both of these types of information on Kiruna's decision making process.

4.2 Perfect Information

Perfect information is information that is 100% correct, 100% of the time. Though there is little chance of obtaining a source of perfect information, considering the possibility allows decision makers to examine how much better off they would be if they made their decision after they knew what outcome would occur. Suppose the mine is offered a scanner that can predict with certainty which type of ore is delivered to the crusher. Once the mine operators receive the information on the extracted ore type from the perfect scanner, they decide to which crusher to send the train. Figure 4.2 illustrates the case of perfect information.

In the decision tree in Figure 4.2, there are four decisions the mine operators can make. The first three branches emanating from the decision node represent the base case scenario. The fourth branch represents the alternative to acquire perfect information. Mine operators make a decision on whether to direct the ore to a certain crusher based on their expectation of the ore type contained in the train or to obtain perfect information on the contents of the train load. Before the perfect information source is used, there is an 85% chance it predicts B1 ore, an 11% chance it predicts B2 ore, and a 4% chance it predicts D3 ore. These percentages are the conditional probabilities of the occurrence of the three ore types given the expectation that the ore type is B1. Since these probabilities were not known at the time of extraction, we assume they are the same as the probability of the realization of the three ore types when a suspected load of B1 ore arrives at the crushers, as calculated for the base case scenario. Once the mine operators receive the scanner results, the ore type is known and there is no uncertainty associated with the decision as to which crusher to send the ore.

The expected value of perfect information (EVPI) is the difference between the expected value of the best alternative without information and the expected value of the information alternative. The expected value of the information is $0 per train load (because that is the alternative with the lowest cost, as shown in Figure 4.2), thus making the EVPI equal to $1,094 per train load.

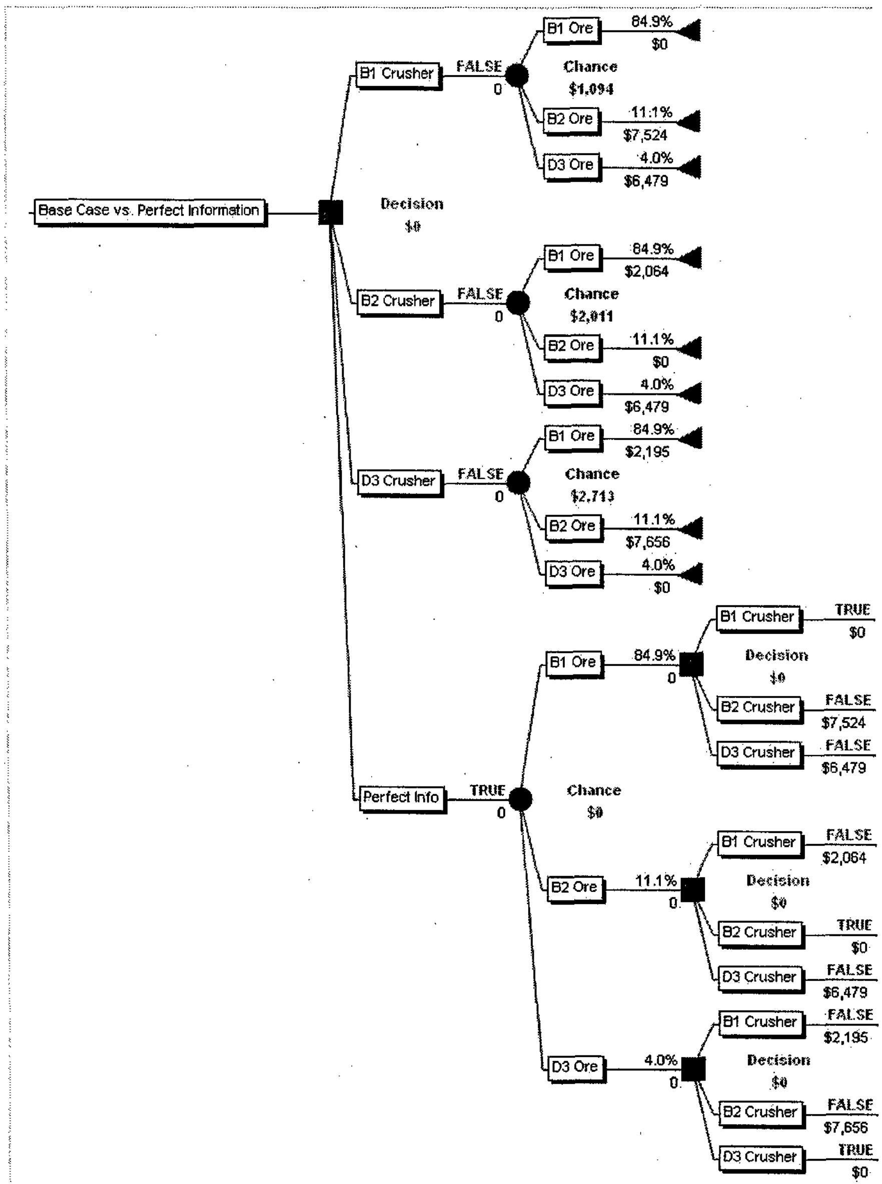

Figure 4.2. **Base Case vs. Perfect Information**. This decision tree is a comparison between the original set of decisions and uncertainties mine operators face plus the additional decision of utilizing a source of perfect information. This information source allows mine operators to answer the following question: how much better off would we be if we knew the ore type with certainty before we direct the ore load to a crusher?

If the mine managers are offered a perfect scanner, they should pay no more than the equivalent of $1,094 per train load for it. However, scanner technology is not a source of perfect information. A scanner that is not accurate 100% of the time is a source of imperfect information.

The following section discusses an available scanning system and the expected value this imperfect information source provides to the mine.

4.3 Laser-Induced Fluorescence (LIF) Analyzer

The use of laser-induced fluorescence (LIF) in the mineral industry is a recent development. AIS Sommer GmbH of Germany introduced the first LIF analyzer to the mining sector in April 1998 (Broicher, 2000). LIF technology takes advantage of photoluminescence, a physical property of minerals. Photoluminescence is when matter emits visible radiation after it has been irradiated with light. In the case of LIF technology, the light source is a laser. The wavelengths of the visible radiation emitted are unique to trace elements that are present in the mineral being scanned.

4.3.1 Advantages and Disadvantages of LIF Technology

One of the major disadvantages of LIF analysis is that it is limited to sampling only the surface of a load of ore. Users assume that the surface scan is representative of the entire load; that is, that the load is homogeneous throughout. Another disadvantage to LIF technology is the difficulty in determining elemental composition of heterogeneous rock. The many different trace elements tend to blend together in a cumulative emission spectrum, thus making it nearly impossible to identify individual elements present in the mineral (Broicher, 2000).

Despite these drawbacks, there are also many advantages to using LIF technology for mineral analysis. LIF can be utilized on most minerals and rocks. The irradiation of the mineral takes only a few nanoseconds; thus the total sampling of a mineral will take less than 10 nanoseconds. As many as 500 samples per second can be realized. The speed in acquiring results is limited by the sample evaluation software. LIF is an optical sampling technology. This is an advantage because there is no need to gather samples and destroy material to realize elemental composition. Additionally, LIF analysis can be utilized over varying distances, resulting in more flexibility in its use (Broicher, 2000).

4.3.2 LIF Analyzers at Kiruna

The first use of LIF technology in the mineral industry was the result of a joint effort between LKAB and AIS Sommer GmbH. There have been a number of tests utilizing the LIF scanner conducted at Kiruna. The mine has tested the LIF analyzer in the production area, above a conveyor in one of the ore processing mills, and in the main haulage level. The first test of the LIF technology at Kiruna was conducted from March - May 1998. The LIF unit was suspended in one of the sublevels in the production area (see Figure 2.1). The Load-Haul-Dump units (LHDs) drove under the LIF which scanned the bucket load of ore. An engineer also took physical samples of the ore in order to check the accuracy of the unit. This unit was returned to the manufacturer after the test period to improve its durability for the rough mining environment. In February 1999, a second LIF test unit was installed in the processing plant over the belt conveyor. After two months of continuous operation, the unit failed and was returned to the manufacturer for further improvements.

In 2000, a new company was formed which specialized in applying LIF technology to the mining sector. Their first LIF analyzer was delivered to Kiruna in May 2001 and was tested both above a conveyor belt and in the production area. In August 2001 it was returned to the manufacturer for further improvements. The analyzer was returned to Kiruna in November 2001 where it was tested in the main haulage level. The analyzer was suspended above the train tracks and scanned the ore as the trains passed underneath on the way to the crushers. With these sample results mine operators could redirect the train to the appropriate crusher if necessary. This unit was returned to the manufacturer for final test work. A LIF scanner was re-installed in the main haulage level in December 2003 and was discontinued approximately 7-8 months later due to technical difficulties.

4.3.3 Positioning the LIF Analyzer

There are advantages associated with locating the LIF scanner on the main haulage level. First, one scanner can be used to analyze all ore collected from the mine, regardless of the production area from which it was extracted. Second, installation of the LIF scanner on the main haulage level provides mine operators with some advance notice as to the content of the train load before it arrives at the crusher. The scan provides the mine operators with an estimate of the phosphorus level in the train, thus allowing them to redirect the train to the appropriate crusher based on the information provided from this scan. However, there are also disadvantages to having the LIF analyzer installed on the main haulage level.

The first major disadvantage is the quantity of ore being scanned. A train typically carries about 450 to 500 tons of ore. The scanner only has the ability to scan the surface of the ore in the train, leaving a large margin for error if there is variation in the phosphorus content in each train car. If the LIF analyzer were installed in the production area, it would only scan an LHD bucket load, which holds approximately 25 tons of ore. While there is still a portion of ore in the bucket load that cannot be analyzed, there is a greater chance that the bucket load is more homogeneous than a train load of ore carrying 500 tons.

Another disadvantage of positioning the scanner on the main haulage level is the timing of the analysis. Even though mine operators can redirect the trains to the appropriate crusher based on the LIF scans, there is still the possibility of incorrectly dumping ore into the orepasses in the production area. Installing the scanner in the production area will allow earlier scanning of the collected ore, leading to a smaller probability of incorrectly dumping ore into the orepasses, thus leading to a higher probability of collecting the ore needed to meet production targets.

4.4 Imperfect Information

Information sources are usually subject to errors; therefore, the information they provide is not perfect. For example, though the scanner indicates the LHD bucket contains B1 ore, there is some probability that the reading is wrong and the ore is actually B2 or D3. The accuracy of the scanner influences the value of the scanner to the mine, which influences the purchasing decision.

The accuracy of the scanner is represented by the conditional probabilities at the end of each branch indicating the realized ore type after the ore has been sent to a crusher (see [1] on Figure 4.3). These conditional probabilities are interpreted as the probability the ore type is B1, B2 or D3 given the scanner predicts it is B1, B2 or D3. Since we were unable to obtain actual scanner accuracies for the given scenarios, we have chosen some representative scanner accuracies given our discussions with one of the initial developers of the scanner, Herb Broicher, and the head of the LKAB LIF research group, Niklas Johansson. For example, the probability the ore type deposited into the B1 crusher is B1 given the scanner predicted it would be B1 is 90%, as shown below.

P(B1 ore|scanner predicts B1 ore) = 90%

We use the following methodology to compute the probability that the ore is B2 given the scanner predicted B1 and the probability the ore is D3 given the scanner predicted B1. We have assumed that in the event that the scanner predicts the ore load contains B1, the ore type is actually B1 90% of the time. We then proportion the remaining 10% probability between the realizations of B2 ore and D3 ore given the scanner predicts B1 (see [1] on Figure 4.3). We would expect the realization of B2 to be higher than the realization of D3, so we put an initial guess for the probability of B2 or D3 ore given the scanner predicted B1. We then take the ratio of the probability on the B2 branch to the sum of the probabilities on the B2 and D3 branches, which is 0.667. We then establish the relationship between the B2 and B1 branch as follows:

$$\mathrm{P(B2\ ore \mid scanner\ predicts\ B1)} = (1 - \mathrm{P(B1\ ore \mid scanner\ predicts\ B1)}) * 0.667$$

The calculation for the realization of D3 ore given the scanner predicts B1 is:

$$\mathrm{P(D3\ ore \mid predict\ B1)} = 1 - \mathrm{P(B1\ ore \mid predict\ B1)} - \mathrm{P(B2\ ore \mid predict\ B1)}$$

A similar methodology is used to construct the remaining conditional probabilities given the scanner predicted either B2 or D3 ore. The conditional probabilities for each branch are listed in Table 4.1.

Scanner Prediction (1)	**Ore Type Realization** (2)	**Conditional Probability** (3)
B1 Ore	B1 Ore	.90
B1 Ore	B2 Ore	.067
B1 Ore	D3 Ore	.033
B2 Ore	B1 Ore	.075
B2 Ore	B2 Ore	.90
B2 Ore	D3 Ore	.025
D3 Ore	B1 Ore	.02
D3 Ore	B2 Ore	.08
D3 Ore	D3 Ore	.90

Table 4.1. **Conditional Probabilities of Scanner Predictions.** Column one (1) is the ore type the scanner predicts. Column two (2) is the actual ore type of the load. Column three (3) is the conditional probability that the ore type is (2) given the scanner predicted (1). That is, (3) = P[(2) | (1)].

For readability we display a partial representation of the imperfect information tree in Figure 4.3. A full representation can be seen in Appendix C. The top branch represents the best alternative without information from the base case. The bottom branch is the alternative of using a scanner to predict the ore type in the current train load. The LIF analyzer scans the ore and there is a chance it predicts B1, B2 or D3 ore. After this prediction is made, the mine operators decide to which crusher to send the ore. We only show the decision alternatives given the scanner predicts the train load contains B1 ore. The other two branches (that the scanner predicts B2 or D3 ore) are collapsed and the expected cost of each decision is labeled beside the collapsed branch.

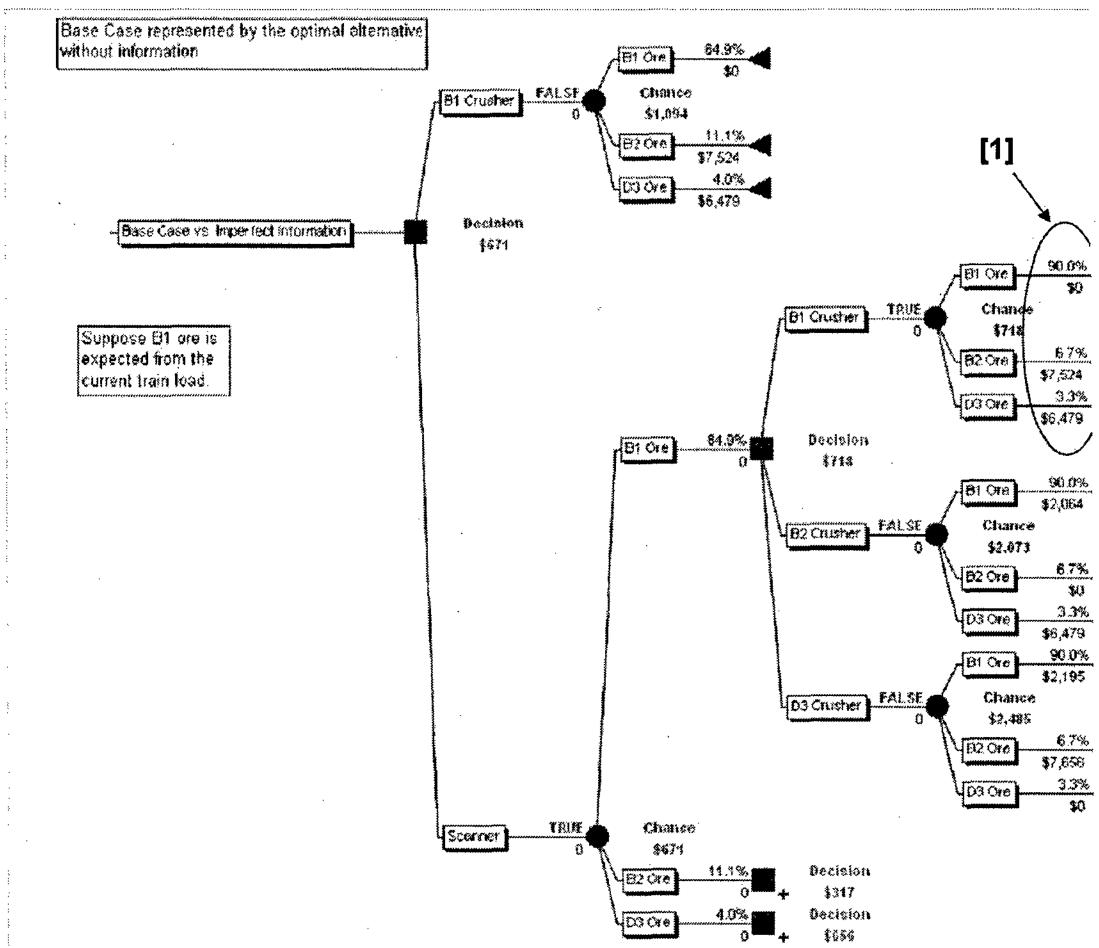

Figure 4.3. **Base Case vs. Imperfect Information**. In this decision tree the mine operators can make a decision to use a source of imperfect information, that is an information source that is subject to errors.

Taking the product of 1) the probability of the scanner predicting each ore type and 2) the associated value of that decision, the expected value of the scanner information is \$671 per train load. Taking the difference between the expected value of the best alternative without information (\$1094) and the expected value of the scanner (\$671), we calculate the expected value of imperfect information (EVII) as \$423 per train load. That is, if the mine's decision makers can obtain the scanner for less than the equivalent of \$423 per train load, the scanner presents some value to them.

Since we constructed these probabilities based on personal communication, we conduct a sensitivity analysis of the accuracy of the scanner for each ore type. This sensitivity analysis provides mine operators with a range of scanner accuracies over which it is beneficial to purchase the scanner.

4.5 Sensitivity Analysis

The B1 ore is the most susceptible to misclassification errors and, consequently, the most likely to show deviation from its production target. Therefore, we complete a sensitivity analysis of the reliability of the scanner in predicting B1 ore. The sensitivity analysis indicates the lowest reliability (accuracy) of the scanner that is still beneficial to the mine. Once the expected value of the imperfect information reaches \$0 per train load, the information from the scanner offers no benefit beyond the original decision the mine operators make. While conducting this sensitivity analysis, the reliability of the scanner predicting B2 or D3 ore is held constant at 90%.

We use the PrecisionTree software sensitivity analysis toolkit to perform the analysis. We vary the reliability of the scanner between 50% and 100% and look for the point where the EVII first hits \$0. Figure 4.4 details the results of this sensitivity analysis.

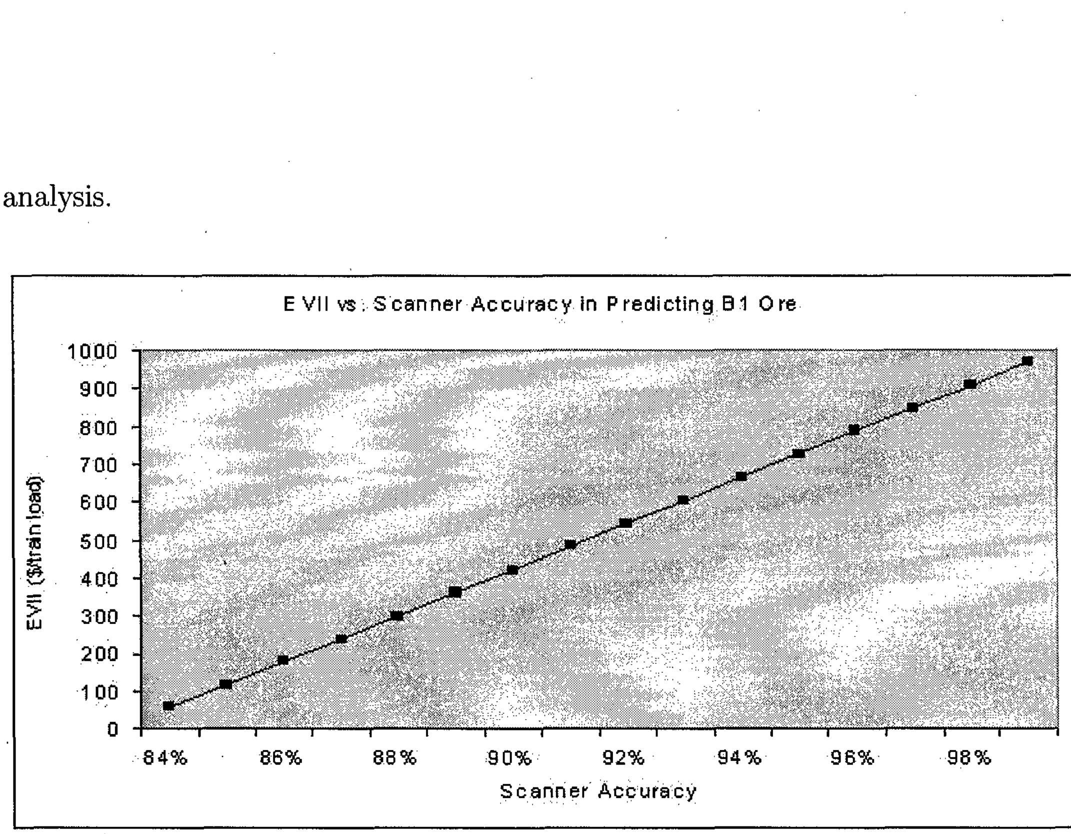

Figure 4.4. **Relationship between the Reliability of the Scanner and the Expected Value of the Imperfect Information Source**. This graph details the effect of changing scanner accuracy on the expected value of the imperfect information source. At 83% accuracy, the EVII is $0, meaning the scanner is no longer accurate enough to benefit the mine in reducing ore misclassifications.

We see in Figure 4.4 that once the scanner reaches 83% accuracy, the EVII is $0. When the expected value of imperfect information is zero, the expected value of the cost of the information is the same as the expected value of the cost of the best alternative without information; therefore, it is best for the mine not to purchase the scanner and continue with its current policies.

4.6 Results

The results of the sensitivity analysis, coupled with the initial evaluation of a LIF analyzer that provides imperfect information to the mine if it is purchased and installed in the production area, allows us to determine if buying this scanner is worthwhile to the mine by comparing the expected value of purchasing the scanner (expected value of imperfect information) to the costs of the scanner. If the cost of the scanner is greater than the expected value gained from its use, the mine should not buy the scanner. If the expected value of the scanner is greater than the costs, the mine should purchase it. The purchase cost of a scanner for the Kiruna mine is approximately \$355,222 and the annual maintenance of a scanner is usually estimated at 10% of the cost, or \$35,522 (Broicher, 2005).

Our recommendation is that a LIF analyzer be installed in each of the 10 production areas in the mine (reference Figure 2.3, Section 2.4). We calculate the present value of the cost of the scanner over a three year period assuming a discount rate of 10%, which results in a cost of \$452,394 per scanner. The purchase of 10 scanners results in the total cost over the three year period to be \$4.5M. Similarly, we can calculate the present value of the benefit of the EVII.

We calculated the expected value of the imperfect information alternative as \$423 per train load (see Section 4.4). We convert the EVII from dollars per train load to dollars per year by multiplying the EVII times 125 trains per day and then by 365 days per year. This results in a benefit of \$19.3M per year. We perform the present value calculation over the three year period with a discount rate of 10%, which results in a total benefit of \$52.9M over the three year horizon. Since the expected benefit is much higher than the expected cost (\$4.5M), we conclude there is positive value associated with the decision to purchase a scanner for each production area, given the assumption of the accuracy of the scanner.

In Section 4.5 we established the scanner information was of positive value (positive EVII) to the mine when the scanner was between 84% and 100% accurate in

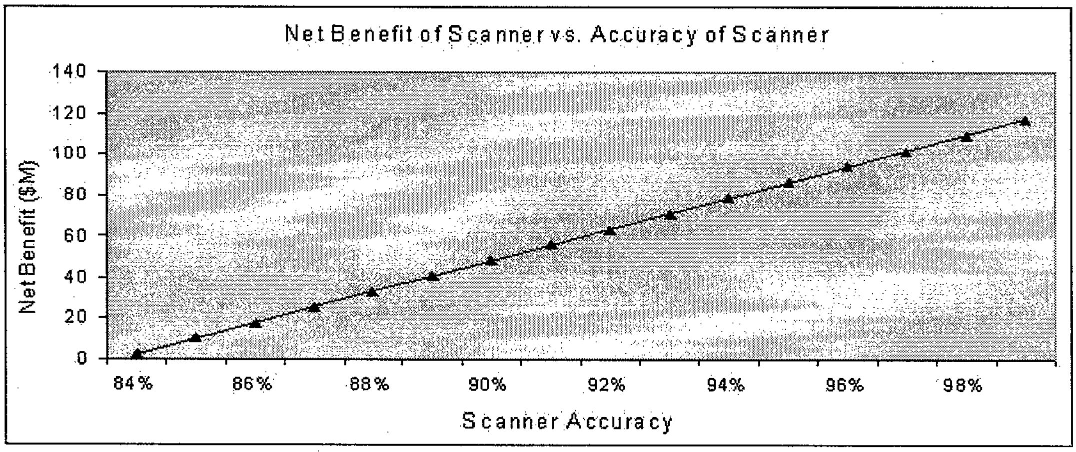

Figure 4.5. **Effect of Scanner Accuracy on Net Benefit.** Using the range of scanner accuracies where the scanner has positive value to the mine, we establish a relationship between the accuracy of the scanner in predicting B1 ore and the total net benefit to the mine. The net benefit is the difference between the expected value of imperfect information and the purchase cost and yearly maintenance of the scanner.

predicting B1 ore. We can calculate the net benefit of the scanner to the mine over a three year horizon for each of these values. Figure 4.5 represents the relationship between the scanner accuracy and the net benefit of the scanner to the mine over this range.

Given our assumptions about the accuracy of the scanner, we show that there is positive benefit to the value of acquiring additional information regarding the phosphorus content in the extracted ore. This additional information helps eliminate some of the uncertainty surrounding which ore type is in the current train load. Since we do not have exact numbers for the accuracy of the scanner, we report a bound on the reliability of the scanner, below which the value of obtaining additional information is zero. Comparing the benefit of the scanner to the purchasing and maintenance costs over a three year period, at a 10% discount rate, we can inform mine decision makers that there is positive value associated with the purchase of the scanners. Specifically, referencing Figure 4.5, the positive value of the scanners range anywhere from $2.7M per year to $116M per year, depending on the accuracy of the scanner.

Chapter 5

RESULTS AND CONCLUSIONS

In our research we have studied the effect of dilution on extracted ore grade quality at LKAB's Kiruna iron ore mine located in northern Sweden. Specifically, we have investigated the implication of misclassification of ore and presented a value of information framework to analyze the possibility of the Kiruna mine purchasing scanner technology. This technology would provide information on the phosphorus level of the extracted ore, thus reducing the occurrence of ore misclassifications.

We developed a methodology that allowed us to identify misclassification errors in the extraction data file. Kiruna provided us with this data file which chronicles all ore extractions from September 2001 to June 2004. We associated a cost with the misclassification errors in terms of the under-utilization of the ore processing mills. This cost consisted of profits forgone from misclassified ore, and fixed and variable costs associated with the under-utilization of the mills. We used a decision tree to model the Kiruna mine operator's current decision as to which crusher to direct a train load of ore and to model uncertainty of the ore type deposited into the crusher. We then analyzed the possibility of utilizing a LIF (laser-induced fluorescence) scanner to reduce the uncertainty in the extracted ore type. In the remainder of this chapter we summarize the results of this analysis and the implications, limitations, strengths, and possible extensions of our research.

5.1 Results

In Chapter 4 we found that, given our assumptions about the Kiruna decision-making process, there is positive value associated with the purchase of an LIF scanner. In our analysis, we specifically looked at the accuracy of the scanner in predicting the B1 ore type. Our initial investigation of the expected value of the scanner indicates that if we assume the probability the ore type is B1 given the scanner predicts B1 ore is 90%, there is benefit gained from purchasing the LIF scanner. The expected value of the imperfect information source (the scanner), or EVII, is \$423 per train load.

We conducted a sensitivity analysis on the accuracy of the probability the ore type is B1 given the scanner predicted it would be B1. We found that if the probability the ore type is B1 given the scanner predicts B1 ore is greater than or equal to 84%, then the EVII is positive. If the scanner accuracy is less than 84%, the information from the scanner would no longer be valuable to the mine (EVII $\leq$ \$0).

Once we calculated the expected value of the scanner and established a range in which the reliability of the scanner presents positive value, we compared the benefit received from the scanner to the costs of purchasing and maintaining 10 scanners, one in each production area. We compared the expected benefits and costs of the scanner over a three year period using a discount rate of 10%. The net benefit of the scanner to the mine ranges from \$2.7M (84% accurate) to \$116M (99% accuracte).

5.2 Conclusions

There are a number of conclusions that can be drawn from this research. We start with a discussion of the implications of this research, then address the limitations and strengths of our methodology. Finally, we conclude with some future research and proposed extensions.

5.2.1 Implications

We have developed a methodology that allows the Kiruna mine to scientifically analyze the choice of purchasing a technology that would gather additional information on the phosphorus level in its extracted ore. We present the mine managers with the results that inform them of their expected benefits given the opportunity to purchase a scanner within a certain reliability range. Given this information they can determine whether or not this reduction in uncertainty is economically beneficial to them.

This research is the first implementation of a value of information framework applied to the mining sector. Our methodology presents the mining sector with a methodology that considers uncertainty in decision making. It provides a suggested method to quantify and qualify uncertainty and determine if gathering additional information to reduce that uncertainty will be of economic benefit to a mine.

5.2.2 Limitations

One limitation with our chosen modeling and analysis method is that it is a static analysis. We consider the instant immediately before a train arrives at the crusher. The only decision the mine operators must make is to which crusher to direct the ore based on their assumption of the ore type in the train. In reality, there are a number of other factors that also influence the mine operators' decisions. One such factor is the current level of production for each of the ore types. The relative levels of production between ore types can influence the mine operators' decision regarding to which crusher to send the ore. If the mine operators suspect they will easily make their monthly production target for B1, they may start to direct some of the B1 ore loads to the B2 and D3 crushers in order to assist in meeting the monthly production targets for those ore types. This decision is contingent on keeping the average phosphorus levels in each ore type within desired limits.

Mine operators also redirect ore to a crusher for reasons not captured in the misclassification methodology we developed. We have identified three causes for misclassification. There are other instances of misclassification that we may not have captured because these decisions are not readily reflected in the ore extraction data set. For example, equipment failures upstream (ore lifts to the surface, train transport on the surface, etc.) can cause mine operators to redirect the ore. The ore extraction data set only records data about the ore dumped into the crusher; any operations upstream are not captured in the file. To the best of our knowledge we have detected all misclassification errors that we could with the extraction data file.

Another factor we do not consider is the movement of ore from the mine to the mills. We have assumed that there is a one-to-one correspondence between dumping the ore into the crusher and the mill to which the ore is sent. This is not necessarily the case. There are very costly methods that allow mine operators to redirect some of the ore if it is found to be misclassified. However, the complicated logistics and high costs make redirecting ore highly undesirable. While we realize this movement happens we are unable to capture it with the data available to us. In order to capture ore redirection between mills we would need variables detailing upstream operations such as the lift on which the ore was placed and which mill that lift services.

We also made a number of estimates in our research. Because of aggregate cost data in the Kiruna cost model provided by the World Mine Cost Data Exchange, we had to estimate the fixed cost of ore misclassification for the B1 and D3 mills. The utilization of each of the mills is an estimate based on our calculations of estimated and actual production of each ore type using the extraction data base. Finally, we used discussions with LIF experts to estimate the accuracy of the LIF scanners for our analysis on the value of the scanner information alternative to the Kiruna mine.

We have made a number of assumptions and estimates that have varying effects on our conclusions gathered from the analysis. One assumption is the only cost incurred from ore misclassification is the under-utilization of the ore processing mills. We do not consider other costs such as loss of customer goodwill and ships sitting idle in the harbors. Considering only the under-utilization of the mills presents a lower bound on the cost of ore misclassification. Therefore, our analysis conclusions represent a lower bound on the net benefit of the scanner technology. Quantifying other costs associated with ore misclassification will make the conclusions and recommendations of our analysis stronger. We also made some assumptions on the accuracy of the scanner when conducting the sensitivity analysis. We assumed the accuracy of the scanner predicting B2 and D3 ore types were not affected by changing the accuracy of the scanner in predicting B1 ore. If these assumptions are incorrect, we are unsure of the effects on our conclusions.

Though there are limitations to our modeling method and our evaluation methodology, there are also strengths associated with our modeling technique.

5.2.3 Strengths

One strength of our method of evaluation is its ease of implementation. We mentioned a number of estimates that were made because of lack of complete data. If, in the future, were we presented with actual costs and more precise reliabilities for the scanner, we can easily incorporate these changes into the decision tree by simply changing the costs or probabilities that should be changed. The decision tree then re-computes the expected value of the scanner information and a new expected value of imperfect information (EVII) can be computed.

Another strength with modeling Kiruna's decision using a decision tree is we can run a number of different scenarios if input factors change, or if mine decision makers would like to consider another configuration. For example, the mine plans on changing production to two ore types (B2 and D3) within the next decade. The decision tree could be reconfigured to take this into account by deleting the decision alternative of dumping into the B1 crusher and the outcomes of realizing the B1 ore type. This would allow mine decision makers to resolve some future uncertainty associated with the change in mining practice.

5.2.4 Extensions and Future Research

The methodology developed in this research is not limited to implementation at the Kiruna mine. It can be extended to any mine that encounters uncertainty surrounding its extracted mineral type or quality, even to mines with only one product. The misclassification methodology can be modified to capture instances in which misclassification of any mineral occurs. This misclassification could be that the mineral is not the expected type (as with the Kiruna mine) or it is not the quality expected (it is more diluted than expected).

In addition to this methodology being used in other mining operations with dilution problems, it can also be extended to other mining situations where uncertainty in a concern. For example, equipment failures can severely affect meeting production goals. A value of information methodology could be used to investigate different maintenance strategies for critical mining equipment. A mining company could also evaluate the possibility of purchasing new technology that would more accurately determine the quality of the mineral in-situ, thus resulting in a more precise prediction of extracted mineral quantity and quality.

There are a number of future directions for this research. One direction is to incorporate actual scanner accuracies into the decision tree and rerun the above analysis. This step might involve a joint effort with the developer of the scanner and some laboratory experiments to get a range of reliabilities of the scanner for the three different ore types.

Another direction is to model the mine's decisions and uncertainties when mining two products (B2 and D3). It may be more valuable to revisit this configuration once Kiruna has switched to two products and extraction records can be obtained representing this change. The incidence of misclassification when there are only two products may not be the same as when there are three. This change would also need to incorporate the capacity of the new mill LKAB is building on-site at the Kiruna mine and the ore type it will process.

Our results suggest that there is benefit if Kiruna purchases 10 scanners, one for each production area. This assumes that the incidence of misclassification is the same for each production area. It could be that some areas of the mine are more homogenous in their ore type than others, thus resulting in less incidence of misclassification. Perhaps for these areas, there is no benefit to installing a scanner. Future research could test if variability in ore type at each production area influences the scanner purchasing decision.

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APPENDIX A

COMPARE ACTUAL AND ESTIMATED PRODUCTION FOR B2 AND D3

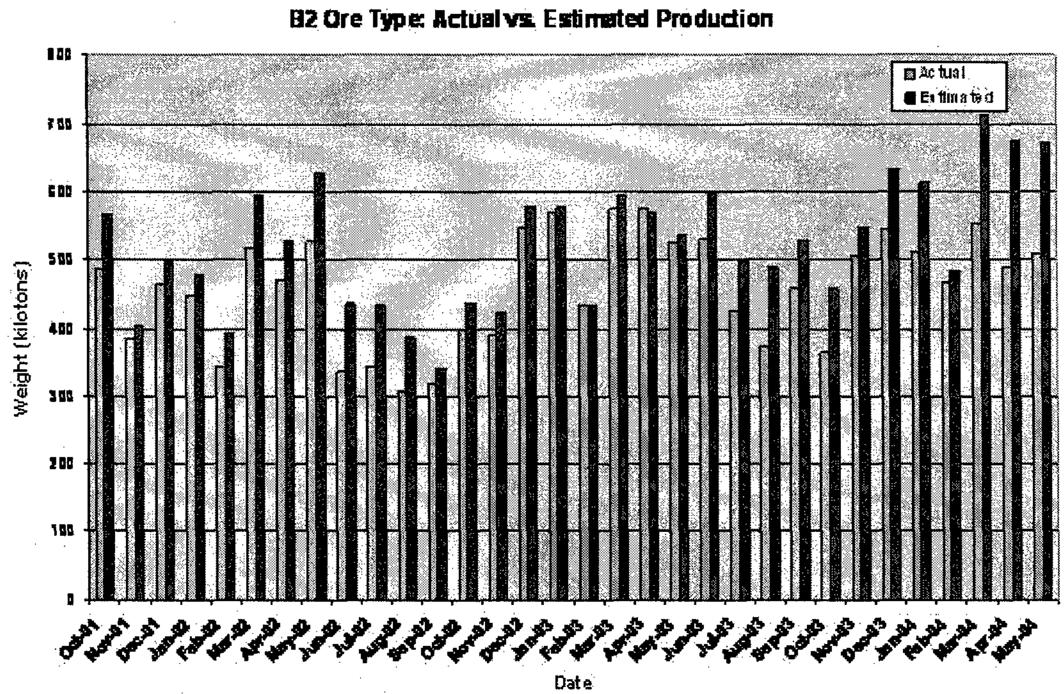

Figure A.1. Comparison of B2 Actual Ore Production and B2 Estimated Ore Production

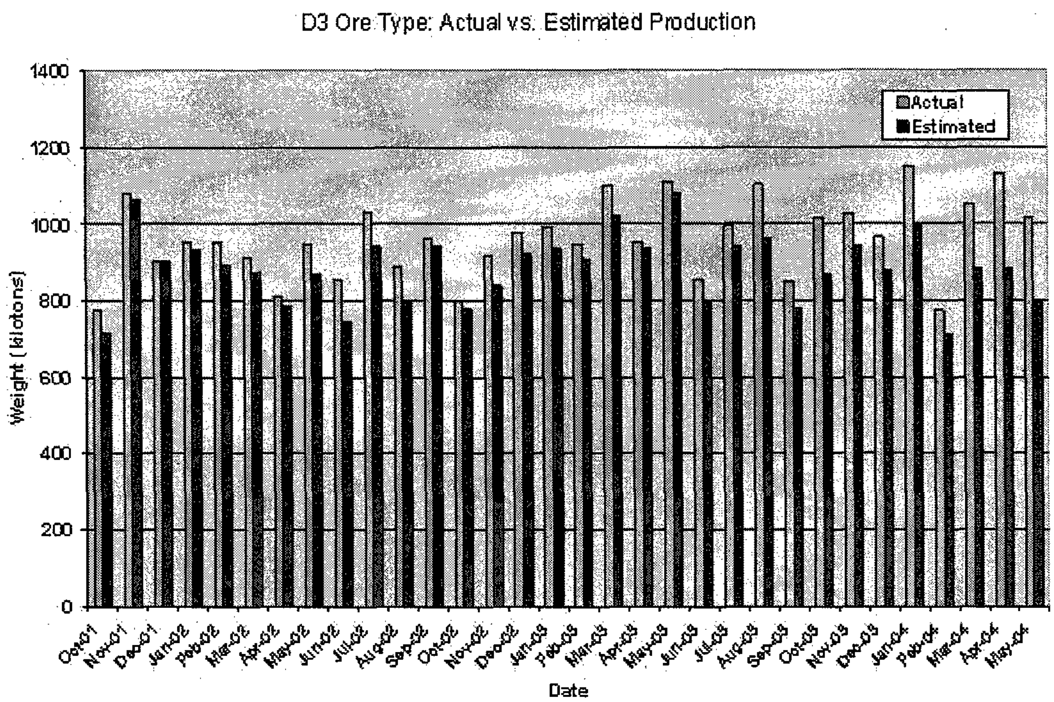

Figure A.2. Comparison of D3 Actual Ore Production and D3 Estimated Ore Production

APPENDIX B

COMPLETE LIST OF KIRUNA VARIABLES

Variable Name	**Label (Description)**
LoadNum	Load Number
Time	Time (24Hr Clock)
Date	Date
TrainNum	Train Number
EngNum	Engine Number
NumCars	Number of Train Cars
PIND	Error Indicator
VIKTIND	Error Indicator
PctWaste	Percent Waste Rock in Ore Load
PctK2O	Percent Potassium Oxide in Ore Load
PctFE	Percent Iron in Ore Load
PctP	Percent Phosphorus in Ore Load
PctMGO	Percent Magnesium Oxide in Ore Load
PctALO	Percent Aluminum Oxide in Ore Load
PctSIO2	Percent Silicon Dioxide in Ore Load
PctCAO	Percent Calcium Oxide in Ore Load
PctTI	Percent Titanium in Ore Load
Weight	Weight of Ore Load
Shift	Shift (FM - day; EM - swing; NAT night)
CrushPckt	Crusher Pocket Number
CrushNum	Crusher Number (4 crushers, 3 active at once)
CrushOre	Crusher Ore Quality (Crusher set to process B1, B2, or D3)
ShaftNum	Shaft Number
ShaftOre	Shaft Ore Quality (Shaft set to hold B1, B2, or D3)
ProdGrpNum	Production Group Number
Status	Status
TransLvl	Transportation Level (1045 m)

Table B.1. Complete List of Variables from Kiruna Ore Extraction Data File

APPENDIX C

BASE CASE VS. IMPERFECT INFORMATION

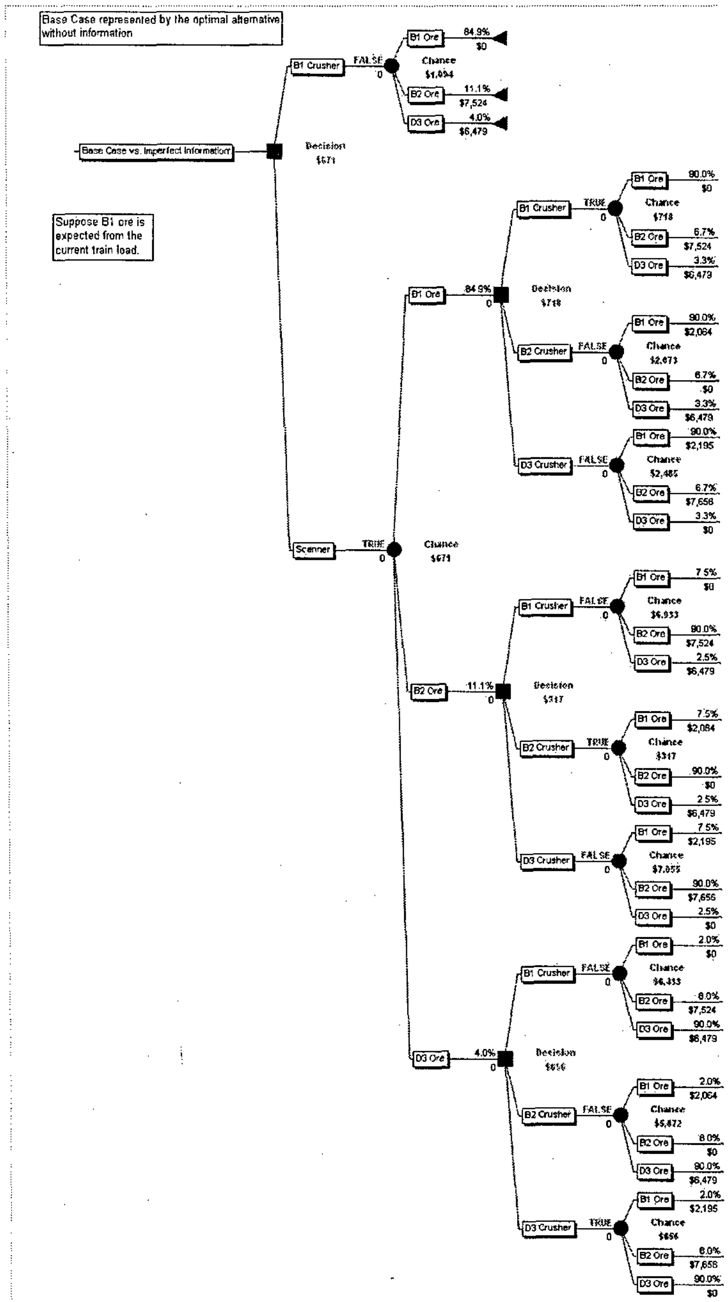

Figure C.1. Base Case vs. Imperfect Information